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THE UNIVERSITY OF ALBERTA

AN APPLICATION OF TIME SERIES ANALYSIS FOR THE IDENTIFICATION AND CONTROL OF A DOUBLE EFFECT EVAPORATOR

by

© HEMANT V. KOGEKAR

A THESIS

SUBMITTED TO THE FACULTY OF GRADUATE STUDIES AND RESEARCH

IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE

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FACULTY OF GRADUATE STUDIES AND RESEARCH

The undersigned certify that they have read, and recommend to the Faculty of Graduate Studies and Research, for acceptance, a thesis entitled AN APPLICATION OF TIME SERIES ANALYSIS FOR IDENTIFICATION AND CONTROL OF A DOUBLE EFFECT EVAPORATOR submitted by HEMANT V. KOGEKAR, B.Tech., in partial fulfilment of the requirements for the degree of Master of Science.

D E Seborg

Supervisor

E. R. Kamens

Date July 8, 1977

To my Father and Mother

ABSTRACT

An experimental investigation was undertaken to evaluate the utility of the time series modelling technique proposed by Box and Jenkins. In this method input - output time series data and their correlation functions are used to develop transfer function models of the process and also of disturbances affecting the process.

Simple dynamic, stochastic models were developed for the evaporator at the University of Alberta using experimental and simulation data. Experimental data was collected using an IBM-1800 process control computer. The effects of feed flow disturbances and the level control constants on both models was studies. Identification was carried out using both open loop and closed loop data. The results of the identification study demonstrated that almost identical transfer function models can be obtained from open and closed loop data.

Using these dynamic stochastic time series models, minimum mean square error (MMSE) controllers for product concentration were designed. The performance of these controllers was compared with a well tuned proportional - integral (PI) controller using both stochastic and deterministic disturbances. The simulation study indicated that MMSE controllers generally produce smaller sum of squares of errors for both types of disturbances. For the experimental study the gains of the controllers had to be reduced to produce satisfactory control. Good concentration control was produced in spite of severe periodic vacuum disturbances. The stochastic controllers based on experimental closed loop data produced unstable performance, however

the MMSE controllers designed using closed loop simulation data performed very well. The simulation study also indicates that MMSE control can be successfully applied to the case of setpoint changes.

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CHAPTER ONE

INTRODUCTION

The design of a process control system necessarily involves understanding the dynamic behaviour of the process. The widely used classical control theory ignores the stochastic nature of the disturbances involved in chemical processes. A mathematical model for such processes that can be related to real data must take into account the dynamic relationship between process inputs and outputs and also the noise affecting the system. Such models can be obtained by combining a deterministic transfer function model with a stochastic noise model.

Of the many methods of stochastic model building the "Time Series" technique of Box and Jenkins [1] has gained considerable favour. They use single input - single output, discrete, linear, transfer function models to represent the process and employ a class of statistical time series models known as autoregressive - integrated - moving average (ARIMA) models to characterise the stochastic disturbances in the system. These models are obtained from process input - output data using iterative, non-linear least squares parameter fitting.

Box and Jenkins have shown that a controller which cancels the effect of the forecasted disturbances also minimizes the variance of output deviations from the setpoint (i.e., a minimum mean square error controller). The time series model is used to obtain an estimate of future disturbances.

This thesis presents an application of the time series modelling technique to model the double effect evaporator in the Department of Chemical Engineering at the University of Alberta and to design and implement minimum mean square error controllers. This application involves extensive digital computer simulations and experimental testing on the actual evaporator.

1.1 Objectives of the Study

The objectives of this study are twofold. Although there have been several applications of the Box and Jenkins [1] technique of model building to model various processes [2 - 6], none of these include a detailed evaluation of the effectiveness of this technique. Thus the first objective of this thesis is to extensively evaluate the utility of this model building technique to model interacting, multivariable processes such as the pilot plant, double effect evaporator.

The second objective is to evaluate experimentally the performance of the minimum mean square controller for a wide variety of conditions including various types of disturbances.

1.2 Structure of the Thesis

The thesis is divided into three parts: literature survey, process identification and controller evaluation.

A brief survey of the literature on time series modelling depicting the theoretical development and applications of this technique to various engineering processes is presented in Chapter Two.

Chapter Three contains the results of model identification and estimation for the evaporator system using both simulated and experimental data. The evaporator system was perturbed under various open loop and closed loop conditions to study the dependence of estimated models on these conditions.

In Chapter Four the performance of controllers designed using these models is evaluated using various types of disturbances. Both experimental and simulation results are presented.

The conclusions from this investigation are presented in Chapter Five.

CHAPTER TWO

A REVIEW OF TIME SERIES ANALYSIS

2.1 Introduction

Since Box and Jenkins [1] presented their approach to stochastic time series analysis in 1970, several researchers have investigated this technique for the purpose of identification and control of industrial processes [2 - 7]. In this chapter the Box-Jenkins technique is briefly described and the important steps and equations are presented. Modifications that have widened the applicability of this technique are also included.

Although time series analysis finds extensive applications in economics and other fields for forecasting purposes, this survey is restricted to applications involving the identification and control of chemical processes.

2.2 The Technique of Time Series Analysis

In 1970 Box and Jenkins [1] published a new approach to linear stochastic modelling using statistical time series analysis. The time series considered here are a sequence of values at equally spaced points in time. Box and Jenkins have presented a very straightforward technique for obtaining discrete dynamic process models from the input/output data. This technique consists of a three stage iterative procedure [7]:

1. Identification
2. Estimation or fitting
3. Diagnostic checking

In the identification stage several tentative model forms are obtained from the correlation patterns of the data and prior knowledge of the process. The data is then fitted using efficient methods assuming one such model form to be true. The residual sequence thus obtained is analysed to detect any lack of fit as well as its possible cause and remedy.

Discrete transfer function models are used to describe the process dynamics and a class of time series models known as autoregressive - integrated - moving average models (ARIMA) are used to characterise the noise.

The input/output relation can be written as,

$$Y_t = \delta_1 Y_{t-1} + \delta_2 Y_{t-2} \ldots\ldots + \delta_r Y_{t-r} + \omega_o X_{t-b}$$

$$- \omega_1 X_{t-b-1} \ldots\ldots - \omega_s X_{t-b-s} + N_t \qquad (2.1)$$

where,

Y_t = value of output deviation from steady state value at time t,

X_t = value of input deviation from steady state at time t,

N_t = deviations in the output due to noise,

a_t = zero mean white noise,

b = time delay expressed as an integer multiple of the sampling interval.

$\{\delta_i\}$ are autoregressive parameters.

$\{\omega_i\}$ are moving average parameters.

Equation (2.1) can be written in operator notation as,

$$Y_t = \frac{\omega_s(B)\, B^b}{\delta_r(B)} X_t + N_t \qquad (2.2)$$

Suppose that the noise signal N_t is represented at the output of a dynamic system whose input is white noise, a_t:

$$N_t = \frac{\theta_q(B)}{\phi_p(B)\nabla^d} a_t \tag{2.3}$$

Then combining eqns. (2.2) and (2.3) gives the general form of the model,

$$Y_t = \frac{\omega_s(B)B^b}{\delta_r(B)} X_t + \frac{\theta_q(B)}{\phi_p(B)\nabla^d} a_t \tag{2.4}$$

where

B = backward shift operator (e.g. $BX_t = X_{t-1}$)

$\omega_s(B) = \omega_o - \omega_1 B - \omega_2 B^2 - \ldots - \omega_s B^s$

$\delta_r(B) = 1 - \delta_1 B - \delta_2 B^2 - \ldots - \delta_r B^r$

$\phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \ldots - \phi_p B^p$

$\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q$

∇ = the difference operator (e.g. $\nabla X_t = X_t - X_{t-1}$)

$\nabla^{-1} = \Sigma$, the summation operator.

In eqn. (2.4) $\delta_r^{-1}(B)\omega_s(B)B^b$ represents the process transfer function model of orders (r, s, b), whereas $\phi_p^{-1}(B)\theta_q(B)\nabla^{-d}$ characterizes the disturbance model, N_t, of model orders (p, d, q). N_t is the consolidated effect of noise from all sources such as other input variables and disturbances. It also represents the effect of modelling errors. N_t and a_t are assumed to be uncorrelated with X_t. Equation (2.4) is represented in block diagram form in Fig. 2.1. It is clear from Fig. 2.1 that N_t represents the value of Y_t when there is no control (i.e. $X_t \equiv 0$).

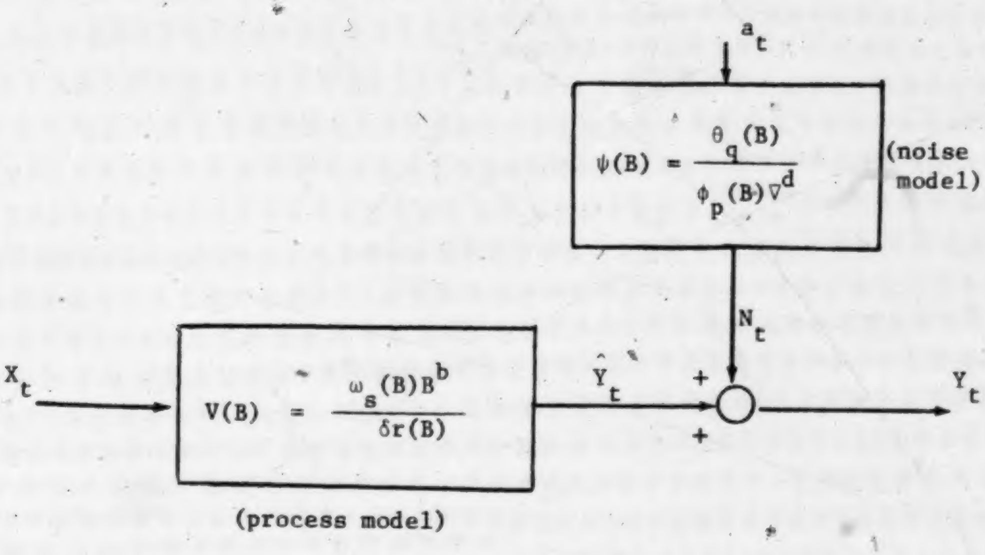
a_t
$\psi(B) = \frac{\theta_q(B)}{\phi_p(B)\nabla^d}$
(noise model)
N_t
X_t
$V(B) = \frac{\omega_s(B)B^b}{\delta r(B)}$
$\hat{Y}_t$
+
+
Y_t
(process model)

FIGURE 2.1 OPEN LOOP PROCESS MODEL

2.2.1 Model Identification

From Fig. 2.1, it follows that

$$\hat{Y}_t = \frac{\omega_s(B)\, B^b}{\delta_r(B)}\, X_t \qquad (2.5)$$

Now $\hat{Y}_t$ can also be represented in a linear filter form as:

$$\hat{Y}_t = V_o X_t + V_1 X_{t-1} + \ldots..$$

$$= (V_o + V_1 B + V_2 B^2 \ldots..) X_t$$

$$= V(B)\, X_t. \qquad (2.6)$$

The linear operator $V(B)$ is the transfer function and the weights V_o, V_1 ..... are called the impulse response function of the system.

Rearranging eqn. (2.5) gives:

$$\delta_r(B)\, \hat{Y}_t = \omega_s(B)\, X_{t-b}\,. \qquad (2.7)$$

or

$$\hat{Y}_t - \delta_1 \hat{Y}_{t-1} - \ldots - \delta_r \hat{Y}_{t-r}$$

$$= \omega_o X_{t-b} - \omega_1 X_{t-b-1} \ldots - \omega_s X_{t-b-s}$$

(2.8)

By comparing eqns. (2.6) and (2.8), the following identity is obtained [1, § 10.2.2] .

$$(1 - \delta_1 B \ldots\ldots - \delta_r B^r)\,(V_o + V_1 B + \ldots\ldots)$$

$$= (\omega_o - \omega_1 B - \omega_2 B^2 - \ldots - \omega_s B^s)\, B^b. \quad (2.9)$$

On equating coefficients of B,

$$\begin{aligned}
V_j &= 0 && j < b \\
V_j &= \delta_1 V_{j-1} + \delta_2 V_{j-2} + \ldots + \delta_r V_{j-r} + \omega_o && j = b \\
V_j &= \delta_1 V_{j-1} + \delta_2 V_{j-2} + \ldots + \delta_r V_{j-r} - \omega_{j-b} && j = b+1, \ldots b+s \\
V_j &= \delta_1 V_{j-1} + \delta_2 V_{j-2} + \ldots + \delta_r V_{j-r} && j > b + s
\end{aligned} \quad (2.10)$$

Equation set (2.10) indicates that if the transfer function model is of orders (r, s, b), then the impulse response weights $\{V_j\}$ consist of:

1. The first b weights $V_o, \ldots V_{b-2}$ are zero.
2. The next s-r+1 values do not follow any fixed pattern.
3. The values of V_j for $j > b + s - r + 1$ follow the pattern dictated by the r^th order difference

equation which has γ starting values,

$$V_{b+s}, V_{b+s-1} \ldots\ldots V_{b+s-r+1}.$$

To obtain consistent parameter estimates it is desirable to have the input X_t's uncorrelated with N_t's. This can be achieved by having an independent random process generating the input signal X_t. When X_t is not a white noise sequence computational simplicity results by "prewhitening". If an appropriate model for X_t is available, then it can be used to transform the auto-correlated input series X_t, into a white noise series, α_t,

$$\phi_x(B)\,\theta_x^{-1}(B)\,X_t = \alpha_t \qquad (2.11)$$

where the model for X_t is

$$X_t = \frac{\theta_x(B)}{\phi_x(B)}\,\alpha_t$$

When such a prewhitened input is used, the V_j weights are proportional to the cross correlation, $\rho_{\alpha\beta}(K)$ [1, p. 380].

$$V_j = \frac{\rho_{\alpha\beta}(k)\sigma_\beta}{\sigma_\alpha} \qquad K = 0, 1, 2 \ldots\ldots \qquad (2.12)$$

where

$$\rho_{\alpha\beta}(k) = \frac{E[(\alpha_t - \mu_\alpha)(\beta_t - \mu_\beta)]}{E(\alpha_t - \mu_\alpha)^2\, E(\beta_t - \mu_\beta)^2} \qquad (2.13)$$

$$E(\alpha_t) = \frac{1}{N} \sum_{t=1}^{N} \alpha_t = \mu_d$$

$$\sigma_\alpha^2 = E(\alpha_t - \mu_\alpha)^2 = \frac{1}{N-1} \sum_{t=1}^{N} (\alpha_t - \mu_\alpha)^2$$

and

$$\beta_t = \phi_x (B)\ \theta_x^{-1} (B)\ Y_t \qquad (2.14)$$

Knowing the V_j's a tentative model form can be identified and initial estimates of the $(r + s + 1)$ parameters can be obtained from the first $(r + s + 1)$ equations in eqn. (2.10).

The identification of the noise model is done using the auto and partial correlation functions of the residuals, $(N_t = Y_t - \hat{Y}_t)$. When the residuals indicate nonstationary behaviour (i.e. an apparently time varying mean) by differencing the residual series one or more times stationary series, N_t', can be obtained

$$N_t' = \nabla^d N_t \qquad d = 0, 1, 2, \ldots.. \qquad (2.15)$$

where, d = degree of differencing.

Auto and partial correlations for this stationary series are then used to obtain a noise model.

A detailed discussion of these identification procedures can be found in Box and Jenkins [1, pp. 174-194 and 377-388] .

2.2.2 Estimation of Parameters

The estimation of parameters is efficiently carried out by minimizing the conditional sum of squares of the residuals.

$$S_o(\underline{\omega}_o, \underline{\delta}_o, \underline{\phi}_o, \underline{\theta}_o) = \min S(\underline{\omega}, \underline{\delta}, \underline{\phi}, \underline{\theta}) \qquad (2.16)$$

where

$$S(\underline{\omega}, \underline{\delta}, \underline{\phi}, \underline{\theta}) = \sum_{t=1}^{n} a_t^2(b, \underline{\delta}, \underline{\omega}, \underline{\phi}, \underline{\theta} \mid x_o, y_o, a_o) \qquad (2.17a)$$

n = number of points in the series

x_o, y_o, a_o = starting values of the series x_t, y_t, a_t

If the first $(u + p)$ values of a_t are assumed to be equal to zero, where $u = \max(b + s, r)$, then eqn. (2.17a) can be written as

$$S(\underline{\omega}, \overline{\delta}, \underline{\phi}, \underline{\theta}) = \sum_{t=u+p+1}^{n} a_t^2(b, \underline{\delta}, \underline{\omega}, \underline{\phi}, \underline{\theta}) \qquad (2.17b)$$

This maximizes the likelihood function of the parameters. Numerical optimization techniques are used to obtain parameter values that minimize the residual sum of squares.

2.2.3 Diagnostic Checking

The parameter fit is quite good if there is no significant cross correlation between the prewhitened input sequence $\{\alpha_t\}$ and the residuals $\{a_t\}$. If the auto and partial correlations of the residuals are within the confidence limits, then the noise model is acceptable. Two quantities $S_{\alpha a}$ and Q_a which are defined below are approximately distributed as χ^2 with f degrees of freedom. They are used to test model adequacy by means of a chi-square test.

$$S_{\alpha a}(f) = n \sum_{k=o}^{K} \rho_{\alpha a}^{2}(k) \tag{2.18}$$

$$Q_a(f) = n \sum_{k=1}^{K} \gamma_{aa}^{2}(k) \tag{2.19}$$

where,

n = total number of data points.

K = number of lags for which the values are calculated.

f = (K + 1) - (r + S + 1) for $S_{\alpha a}$

and f = (K) - (p + a) for Q_a

$S_{\alpha a}$ and Q_a are compared with values in a table of percentage points of χ^2 to obtain an approximate test of the hypothesis of model adequacy. A discussion of these tests can be found in Box and Jenkins [1 p. 392 - 395, 522].

2.2.4 Closed-Loop Process Model Identification

Often process operating data is used in the model identification study. In many cases it is difficult to obtain open loop operating data because open loop conditions may lead to undesirably large deviations and an inferior quality product. Also from a stability point of view, it may not be desirable to operate the plant under open loop conditions.

The problem of identification under closed-loop conditions has been considered by Box and MacGregor [8, 9] and Graupe [10]. They have shown that to identify an unknown system it is often desirable to add an artificially generated signal D_t to the input, X_t. The "dither signal", D_t, is a stochastic sequence with zero mean and is uncorrelated with the error, $e_t = y_t$.

From fig. 2.2, the feedback controller equation is,

$$X_t = C(B)e_t + D_t \tag{2.20}$$

where C(B) is the controller transfer function and

$$e_t = y_t = V(B)\ X_t + \psi(B)a_t \tag{2.21}$$

In eqn. (2.21) y_t is the deviation of output from steady state.

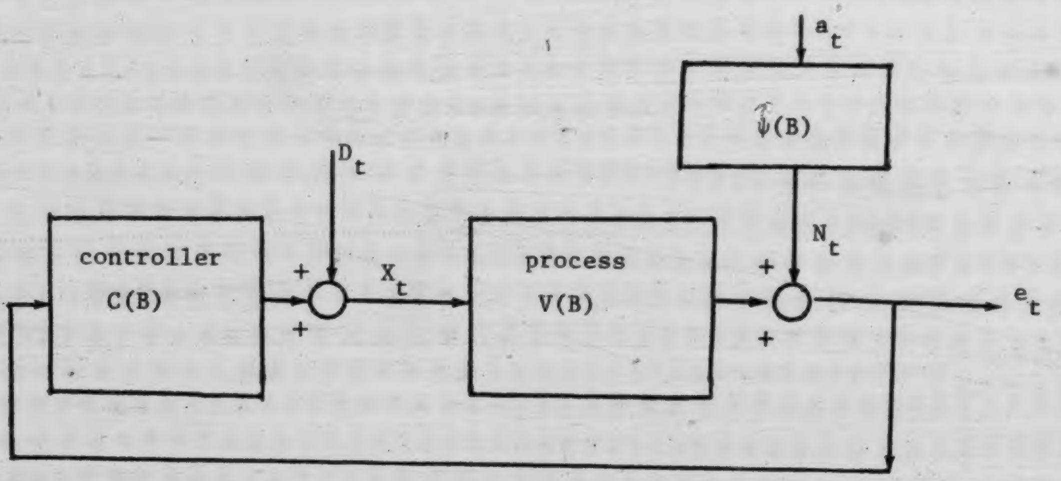

FIGURE 2.2 CLOSED LOOP SYSTEM WITH DITHER SIGNAL, D_t .

Using eqns. (2.20) and (2.21) and substituting for X_t gives

$$1 - V(B)C(B)\ e_t = \psi(B)\ a_t + V(B)\ D_t \qquad (2.22)$$

For the case where $D_t = 0$ and the model orders are not known, then unambiguous identification will not in general be possible. If either V(B) or ψ(B) is known, then using autocorrelations of e_t it is possible to arrive at a correct model for the other one. If the correlation among parameters is high, difficulties can arise which can be greatly simplified by using a non-zero D_t signal [8].

When $D_t \neq 0$, eqn. (2.22) can be rearranged as

$$e_t = \frac{V(B)}{1 - V(B)\ C(B)}\ D_t + \frac{\psi(B)}{1 - V(B)\ C(B)}\ a_t \qquad (2.23)$$

Comparing Fig. 2.3 with Fig. 2.1 it can be seen that for non-zero D_t, a procedure similar to open loop process model identification can be used where the dither signal D_t is treated as an input. Here instead of relying on autocorrelation properties of e_t, the cross correlations between D_t and e_t and the autocorrelation of e_t can be used for parameter estimation.

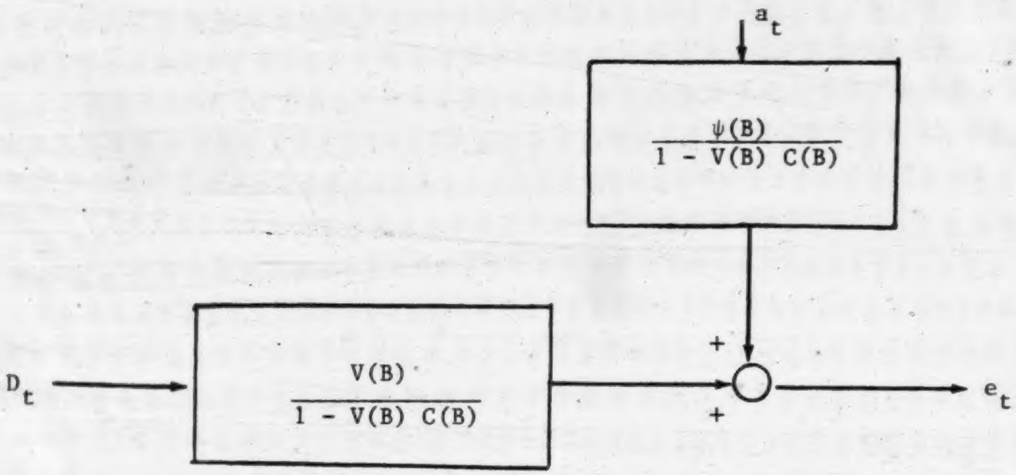
a_t
$\frac{\psi(B)}{1 - V(B)\,C(B)}$
D_t
$\frac{V(B)}{1 - V(B)\,C(B)}$
+
+
e_t

FIGURE 2.3 REPRESENTATION OF CLOSED LOOP PROCESS IN OPEN LOOP FORM.

Hong and MacGregor [5] recommend the use of D-optimal dither signals (signals that minimise the volume of joint confidence region of the parameters) for obtaining better parameter estimates. When the variance of the input or output is constrained, first order autoregressive dither signals with appropriate values of the parameter, ϕ, are shown to be D-optimal.

2.3 Design of a Feedback Controller

Once the noise and transfer function models are obtained, the next step is the design of a controller to maintain the output in proximity of the setpoint value. Box and Jenkins [1, § 12.2] have suggested a procedure to design a controller that minimises the mean square error between output and setpoint.

From Fig. 2.1 it can be seen that for constant input conditions the output deviations in the error are due to disturbance term N_t. Therefore, N_t, represents the total effect of disturbances and the total effect of compensation is the term $\delta^{-1}(B)\ \omega(B)\ X_{t-b}$

If it were possible to set,

$$X_{t+} = \delta(B)\ \omega^{-1}(B)\ N_{t+b} \qquad (2.24)$$

where X_{t+} denotes the calculated control action after the error measurement, e_t is obtained, the effect of disturbance would be cancelled, but since b is positive, the value of N_{t+b} is not available at time t. However by using an estimated or forecast value, $\hat{N}_t(b)$, the minimum mean square error can be achieved.

Let,

$$\hat{e}_{t-b}(b) = N_t - \hat{N}_{t-b}(b) \qquad (2.25)$$

and

$$X_{t+} = -\delta(B)\ \omega^{-1}(B)\ \hat{N}_{t-b}(b) \qquad (2.26)$$

where

$\hat{N}_{t-b}(b)$ is a b step ahead forecast of N_t at time $t-b$ and $\hat{e}_{t-b}(b) = e_t$ is the measured error.

Since

$$N_t = \nabla^{-d} \phi^{-1}(B)\ \theta(B)\ a_t \qquad (2.3)$$

N_t can be written in terms of past, present and future values of a_t as,

$$N_t = \lambda(B)\ a_{t+b} + \eta(B)\ a_t \qquad (2.27)$$

Then,

$$\hat{N}_t(b) = \eta(B)\ a_t$$

$$\hat{e}_{t-b}(b) = \lambda(B)\ a_t \qquad (2.28)$$

From eqn. (2.28)

$$\hat{N}_t(b) = \frac{\eta(B)}{\lambda(B)}\ \hat{e}_{t-b}(b) = \frac{\tilde{\eta}(B)}{\lambda(B)}\ e_t \qquad (2.29)$$

Then the resulting feedback control equation is

$$X_{t+} = -\ \frac{\delta(B)}{\omega(B)}\ \frac{\eta(B)}{\lambda(B)}\ e_t \qquad (2.30)$$

The previous derivation is subject to certain restrictions. It is possible to set

$$X_{t+} = -\delta(B)\ \omega^{-1}(B)\ N_{t+b} \qquad (2.24)$$

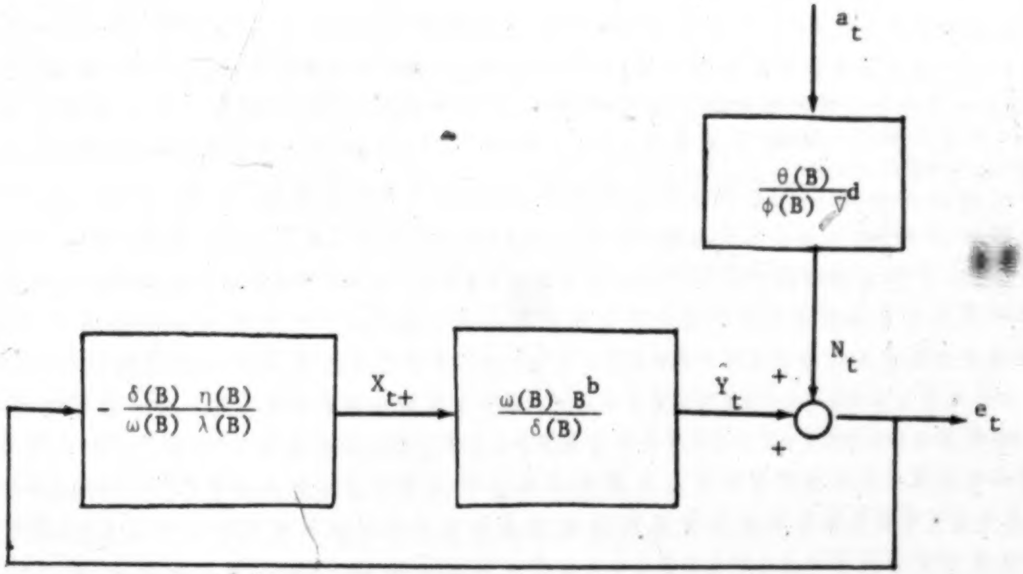
a_t
$\frac{\theta(B)}{\phi(B)\nabla^d}$
N_t
$-\frac{\delta(B)\ \eta(B)}{\omega(B)\ \lambda(B)}$
X_{t+}
$\frac{\omega(B)\ B^b}{\delta(B)}$
$\hat{Y}_t$
+
+
e_t

FIGURE 2.4 MINIMUM MEAN SQUARE ERROR (MMSE) FEEDBACK CONTROL SYSTEM

only when the roots of $\delta(B)$ lie outside the unit circle, or, in other words, when $\delta(B)$ is invertible. Similarly the noise model needs to be invertible, with the roots of $\phi(B)$ lying outside the unit circle.

Further analysis of the minimum mean square error controller indicates that in some cases the MMSE controller will produce large adjustments in the input X_t. This is often the case when the polynomial $\delta(B)$ has a root near the unit circle. Bacon and Howe [3] note that in some cases the MMSE controller can produce unstable system performance even when the process model is known. If large variations in the input cannot be tolerated, redesigning the controller is necessary such that the input variations are constrained at the cost of small increases in the output variance [1, 11, 12] .

2.4 Applications

The Box and Jenkins [1] technique is essentially a "black box" approach; that is, knowledge of the physical process is not necessary for model building. Normal plant operating data can be used to obtain dynamic and noise models. Because of this simplicity of analysis, this technique has been found quite attractive. Several investigations have been carried out to verify the applicability of this procedure to modelling various processes.

Tee and Wu [2] applied this technique to a paper making process. The input variable was the scale reading on the stock gate opening and the output was the basis weight of the paper produced. By keeping a constant gate opening, they developed a disturbance model based on measurements of the basis weight at 20 minute intervals. Later they obtained a combined dynamic and disturbance model, using an experienced operator to perturb the input variable and assuming open loop conditions. A MMSE controller was designed based on this model and it provided improved control over the open loop case.

Restrepo et. al. [13] used this technique to test the feasibility of using time series analysis to model a high order, non-linear system over a wide range of operating conditions.

The system considered was a dynamic model consisting of 20 linear and 10 nonlinear differential equations for a pilot plant scale distillation column with eight sieve trays. This theoretical model was based on physical knowledge of the system. Input-output data was generated from this model to develop transfer function models using the Box and Jenkins technique. The step and impulse responses of these models were found to be extremely close to those obtained using the higher order physical model.

Bacon and Howe [3] assessed the utility of the Box and Jenkins time series modelling technique to model an industrial falling film evaporator system and used the resulting model to evaluate and modify the existing control system. They found this technique adequate to model a full scale chemical process unit in terms of dynamic as well as stochastic relationships. The models thus obtained were very useful in deriving novel control functions that supplement the existing control schemes. However the new control technique was not applied.

The time series technique was used by Wright and Bacon [4] to identify the dynamic behaviour of a laboratory scale heat exchanger network. This system was excited by perturbing the steam control valve position at various inlet water flow rates. The effects of changes in process conditions and process nonlinearities on the estimated models and parameters were studied. Wright and Bacon suggest that experience and basic knowledge of the process must be used to eliminate models which although satisfactory from a statistical point of view are not adequate for physical reasons.

Two applications of model building from closed-loop operating data have been cited by Box and MacGregor [8]. The first one is a polymer viscosity control system. The other an example of a paper making process [2]. Here in an attempt to perturb the system in a random fashion, the experienced operator regulated the stock gate opening, i.e. he acted as a feedback controller [8, 14, 15]. Hence the operating data was analysed once more to obtain models using closed loop methods.

Hong and MacGregor [5] have used the closed loop analysis to model a continuous stirred tank heating process operating under a discrete PI controller. They note that in order to develop confidence in the identified models, the choice of input signal is important.

The sampling interval [16] can also be chosen appropriately to obtain maximum information about the dynamic stochastic behaviour of the process.

Hong and MacGregor [5] and MacGregor et. al [7] have designed stochastic and PI controllers using the identified stochastic models. In an experimental evaluation using stochastic disturbances, these controllers performed better than PI controllers designed using conventional tuning methods.

MacGregor and Tidwell [17] have considered the problem of stochastic control where there are constraints on input variations. They have discussed methods of designing discrete stochastic controllers, which minimise the quadratic cost function, $E\{Y_{t+b}^2 + \lambda X_t^2\}$, for linear processes under stochastic disturbances. Using these methods they designed a controller for the control of viscosity in an industrial polymerization reactor. This controller was found to perform satisfactorily.

A discussion of minimum variance controllers can also be found in [18].

CHAPTER THREE

PROCESS MODEL IDENTIFICATION

3.1 Introduction

This chapter presents the various time series models obtained for the double effect evaporator using both experimental and simulation data. A brief description of the evaporator system and the computer programs used is also presented.

The model identification is discussed in two main parts. The first part (§ 3.4 - 3.6) deals with identification under open loop operating conditions and the second part (§ 3.7 -3.8) deals with identification under closed loop operating conditions. Both parts include simulation and experimental results. Finally, comparisons of process models using open and closed loop operating data are presented in sections 3.7 and 3.8.

3.2 Description of the Evaporator System

Figure 3.1 shows a schematic diagram of the double effect evaporator in the forward feed mode of operation and a conventional multi-loop control system. The eight inch diameter, calandria type, first effect contains thirty-two, 0.75 in. O.D. tubes and operates with a nominal feed rate of 4.5 lb/min of 3 percent aqueous triethylene glycol. It is heated by 1.8 lb/min of saturated steam. The first effect overhead vapour is utilized to heat the first effect bottoms which flows under forced circulation in the three, 6 feet long, one inch O.D. tubes of the second effect. The second effect operates under vacuum. The product is about 10 percent aqueous triethylene

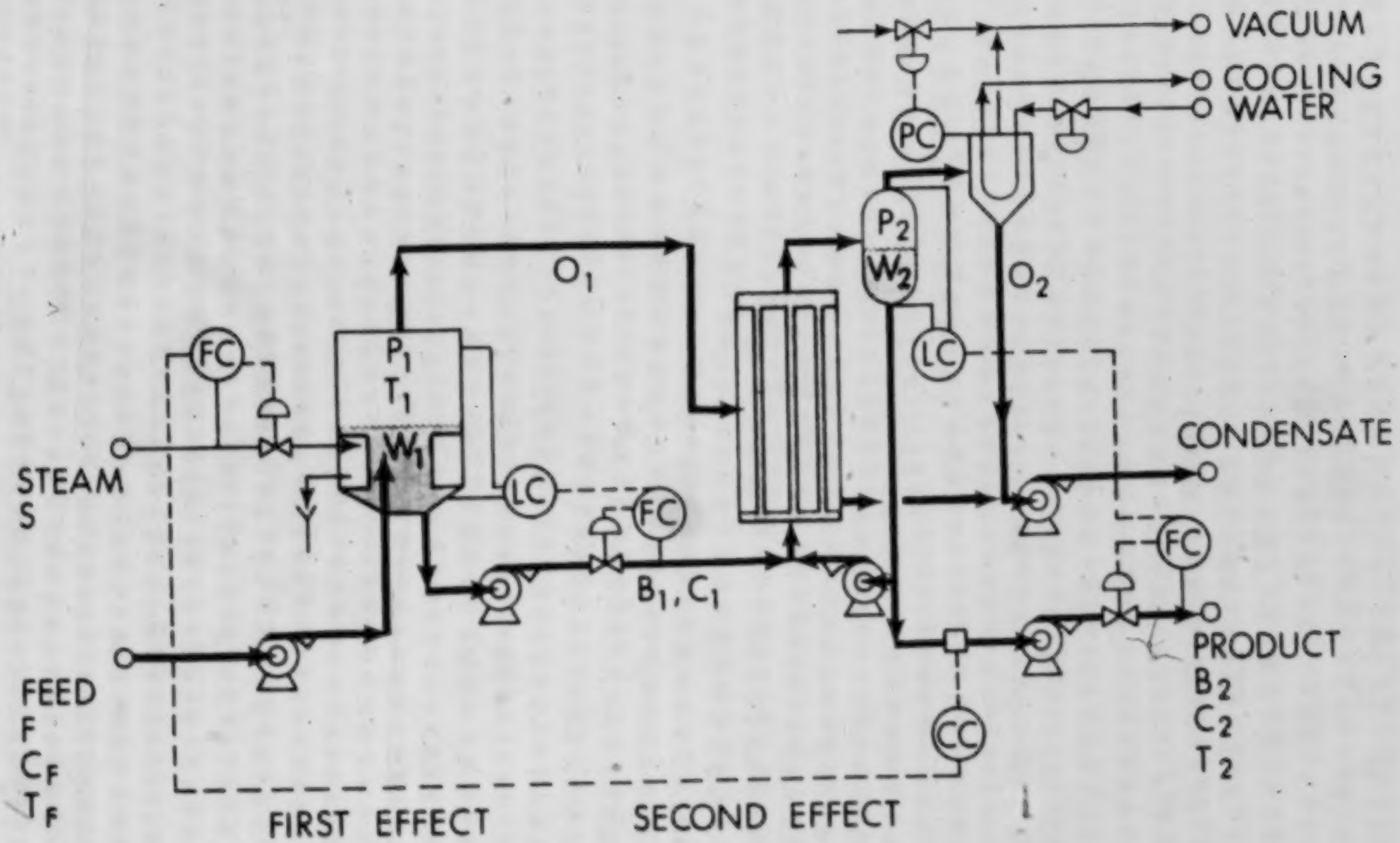

FIGURE 3.1 SCHEMATIC DIAGRAM OF THE DOUBLE EFFECT EVAPORATOR AND A CONVENTIONAL CONTROL SYSTEM.

glycol.

An IBM 1800 real time digital computer is interfaced to the evaporator. Conventional multi-loop control of the evaporator is achieved using the IBM 1800 Direct Digital Control (DDC) package and single and cascaded control loops. Although product concentration, C2, is the most important controlled variable, the liquid levels, W1 and W2, must also be controlled within operating levels. For the present study the liquid levels were controlled by manipulating bottom flow rates, B1 and B2, respectively. The product concentration C2, was controlled by manipulating the flow rate of steam S, into the first effect.

A detailed description of the evaporator system can be found elsewhere [19].

3.2.1 State Space Model of the Evaporator

A number of process models ranging from tenth order nonlinear state space models to the first order transfer function models have been derived for the evaporator by previous investigators. For the present simulation study the discrete, linear fifth order state space model developed by Wilson [20] was used.

This model can be represented as

$$\underline{x}(t + 1) = \underline{\underline{\Phi}}\,\underline{x}(t) + \underline{\underline{\Delta}}u(t) + \underline{\underline{\Theta}}d(t) \tag{3.1}$$

$$\underline{y}(t) = \underline{\underline{C}}\,\underline{x}(t) \tag{3.2}$$

where

$\underline{x}$ is a (5 X 1) state vector

$\underline{u}$ is a (3 X 1) control vector

$\underline{d}$ is a (3 X 1) disturbance vector

$\underline{y}$ is a (3 X 1) output vector

t is the sampling instant

and $\underline{\Phi}$, $\underline{\Delta}$, $\underline{\Theta}$, $\underline{C}$, are constant coefficient matrices of appropriate dimensions.

The variables in eqns. (3.1) and (3.2) are expressed in normalized perturbation form: e.g.

$$x_1 = W1' \triangleq \frac{W1 - W1_{ss}}{W1_{ss}} \tag{3.3}$$

where subscript ss denotes the nominal steady state value. The variables in eqns. (3.1) and (3.2) are defined as follows:

$$\underline{x}^T = [W1', C1', H1', W2', C2']$$

$$\underline{u}^T = [S', B1', B2']$$

$$\underline{d}^T = [F', CF', HF']$$

and

$$\underline{y}^T = [W1', W2', C2']$$

The nominal steady state values and coefficient matrices are presented in Appendix A.

The proportional control law used in the closed loop identification study can be represented as,

$$\underline{u}(t) = \underline{\underline{K}}\ \underline{x}(t) \qquad (3.5)$$

where

$\underline{\underline{K}}$ is a 3 X 5 matrix of controller constants.

3.3 Computer Program for the Simulation Study

The discrete fifth order state space model [20] was simulated on the University's Amdahl-470V/6 digital computer. A program, called SIMUL, was written to simulate the response of the evaporator for various types of disturbances under conventional multi-loop and minimum mean square error (MMSE) controllers. Stochastic disturbances such as Gaussian white noise and first order, autoregressive signals and step changes in load variables were used to evaluate the controllers.

All the relevant state, control and disturbance variables were printed out and punched on cards for use in plotting programs, RBN01 and RBN02 [21].

3.4 Open Loop Identification Studies

For the evaporator system, the most important output variable, C2, is controlled by adjusting the steam flow rate to the first effect. Hence process model identification studies were carried out between input variable, S, and output variable, C2. Both process and noise models were developed for a variety of process conditions. Experimental and simulation runs were carried out for two cases: (i) steam perturbations only, and (ii) simultaneous perturbations of steam flow and feed flow. Thus the feed flow perturbations introduced "noise" into the system.

The perturbation signals consisted of either Gaussian white noise or first order autoregressive noise sequences with zero means and various standard deviations.

The initial model orders and the initial parameter estimates were obtained from the cross correlations between the input and the output and also from the auto and partial correlation functions of the prewhitened series and the residuals. These initial parameter estimates and model orders were then used in a nonlinear, iterative least squares program, TF[1], that minimizes the sum of squares of the residuals. The stopping criterion employed in the estimation program was that the change in the sum of squares of the residuals was less than 10^{-10} or the change in each parameter value of less than 10^{-3}, whichever happened first. 95 percent confidence limits for the parameters were also calculated.

3.5 Identification of Evaporator Models Using Open Loop Simulation Data

Time series models were obtained from data generated from the fifth order state space evaporator model presented in Appendix A. Each run consisted of 320 data points obtained at 64 second intervals.

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[1] A program made available by Dr. J.D. Wright, McMaster University, Hamilton, Ontario.

Since these points covered a time period of six hours, the effect of slower evaporator modes (i.e. large time constants) were fully realized in the input-output series. A large number of data points was used in order to produce small confidence intervals for the parameter estimates. Also the confidence limits on the correlations are narrower (the confidence limits are $\pm 2 \div (\text{number of data points})^{\frac{1}{2}}$).

For purpose of comparison, a theoretical pulse transfer function model was calculated from the discrete fifth order model using the GEMSCOPE program [22]. To check how closely the estimated models agreed with this theoretical model, in some runs parameter estimation was performed using transfer function model orders which were the same as those for the theoretical model. The effect of different model structures and different input signals on the parameter estimates was also studies.

Table 3.1 lists the run conditions for open loop simulation runs SS-1 to SS-6, including standard deviations of the input sequence, σ_{input}, the first order autoregressive filter constant, ϕ_s, and the actual input and output standard deviations. Figure 3.2 presents a base case simulation run, #SS-4, where the two levels are under proportional control using the control law, $\underline{u}(k) = \underline{K}_1 \, \underline{x}(k)$, where

$$\underline{u} = [\,B1' \;,\; B2'\,]^T = [\,u_2 \;,\; u_3\,] \tag{3.6}$$

and

$$\underline{K}_1 = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 3 & 0 \end{bmatrix} \tag{3.7}$$

TABLE 3.1

CONDITIONS FOR OPEN LOOP SIMULATION RUNS

(Steam disturbances, evel control only)

Run No	Steam (lb/min)			Concentration
	σ_{input}	ϕ_S	σ_S	σ_{C2} (% glycol)
SS-1	0.10	--	0.100	0.12
SS-2	0.20	--	0.192	0.21
SS-3	0.20	0.5	0.226	0.42
SS-4	0.32	--	0.308	0.34
SS-5	0.20	0.75	0.294	0.82
SS-6	0.30	0.5	0.340	0.63

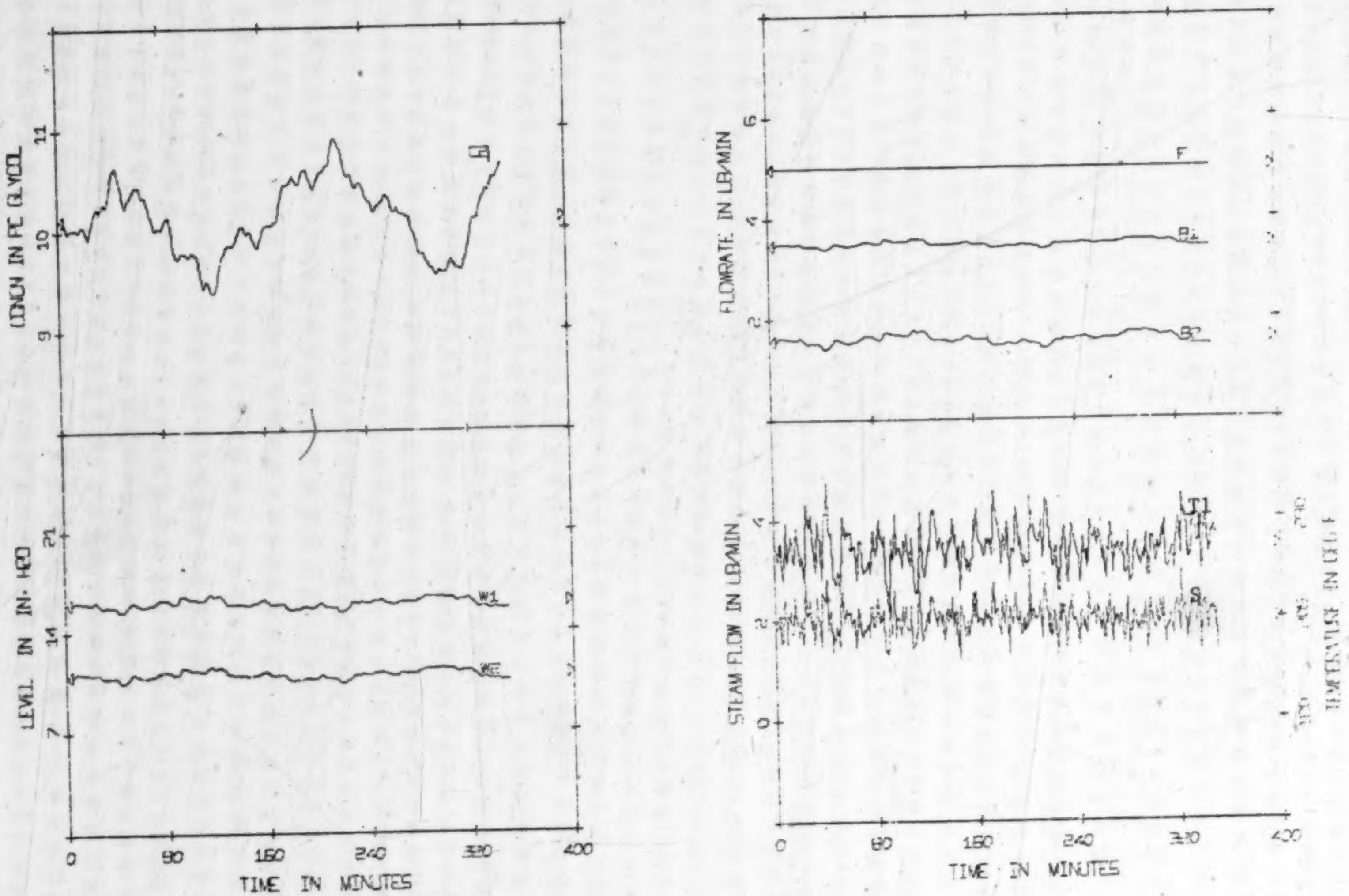


FIGURE 3.2 OPEN LOOP SIMULATION DATA FOR RUN SS-4

In this series of runs, only steam flow rate was perturbed. Table 3.2 compares the parameter estimates obtained using dimensionless x and y for these runs with the theoretical model. Table 3.3 lists parameter estimates and the 95 percent confidence limits for each parameter. Appendix D lists the 95 percent confidence limits for each parameter and also additional models that were fit with their parameter estimates. Only the best fitting models are presented in Tables 3.2 and 3.3.

Note that runs SS-4 to SS-6 have approximately equal input standard deviations but different input series structures. In Figs. 3.3 and 3.4 typical response data for runs SS-5 and SS-6 are presented.

Table 3.4 presents the various run conditions for runs SSF-1 to SSF-4 where both steam and feed flow disturbances were employed. Typical response data are presented in Figs. 3.5 and 3.6. The steam and feed flow disturbances were either gaussian or autoregressive noise sequences. For these runs, two gaussian random number sequences were generated, one for steam and the other for feed flow. The actual disturbance signals were then calculated by passing these sequences through first order autoregressive filters.

Run lengths of 320 data points were selected in order to produce small confidence intervals for the parameter estimates. Since these points cover a time period of six hours (sampling interval = 64 secs.), the effects of the slower evaporator modes (i.e. large time constants) are fully realized in the input-output series.

TABLE 3.2

PARAMETER ESTIMATES FOR OPEN LOOP SIMULATIONS

(Steam Disturbances, Level Control Only)

Run No.	Model	$\hat{\delta}_1$	$\hat{\delta}_2$	$\hat{\delta}_3$	$\hat{\omega}_o$	$\hat{\omega}_1$	$\hat{\omega}_2$	$\hat{\phi}_1$	$\hat{\phi}_2$	$\hat{\theta}_1$	$S_{\alpha a}$	Q_a	Σa_t^2
Theoretical Model	(3,2,1)	2.319	-1.709	0.388	0.0137	0.0013	0.0102	-	-	-	-	-	-
SS-1**	(3,2,1) (2,1,0)	2.319	-1.709	0.388	0.0134	0.0015	0.0078	0.564	0.256	-	44.65*	32.29	0.21×10^{-5}
SS-2**	(3,2,1) (2,1,0)	2.319	-1.709	0.388	0.0134	0.0016	0.0079	0.795	0.053	-	90.62*	26.75	0.47×10^{-5}
SS-3	(3,2,1) (2,1,0)	2.319	-1.709	0.388	0.0139	0.0018	0.0084	0.492	0.439	-	130.66*	50.54*	0.18×10^{-5}
SS-4	(2,1,1) (1,0,1)	1.689	-0.759	-	0.0096	-0.0043	-	0.918	-	0.207	8.67	47.65*	0.338
SS-5	(2,1,1) (2,0,1)	1.548	-0.559	-	0.0103	-0.0156	-	-0.054	0.531	-0.535	12.99	28.66	0.0608
SS-6	(2,1,1) (2,0,1)	1.628	-0.638	-	0.0148	-0.0066	-	-0.318	0.175	-0.474	11.25	34.34*	1.36

* Value of $S_{\alpha a}$ or Q_a larger than $\chi^2_{0.05}$

** Process and noise model parameters were estimated separately.

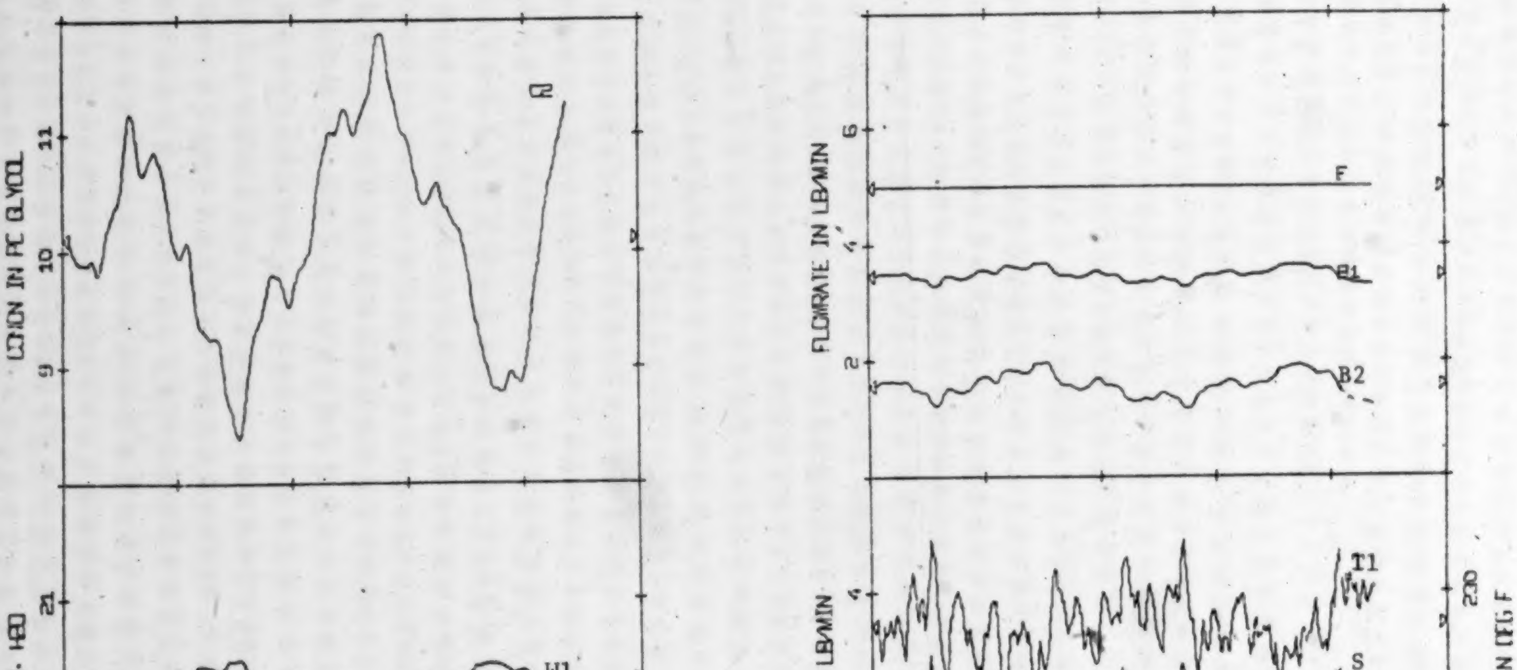


FIGURE 3.3 OPEN LOOP SIMULATION DATA FOR RUN SS-5

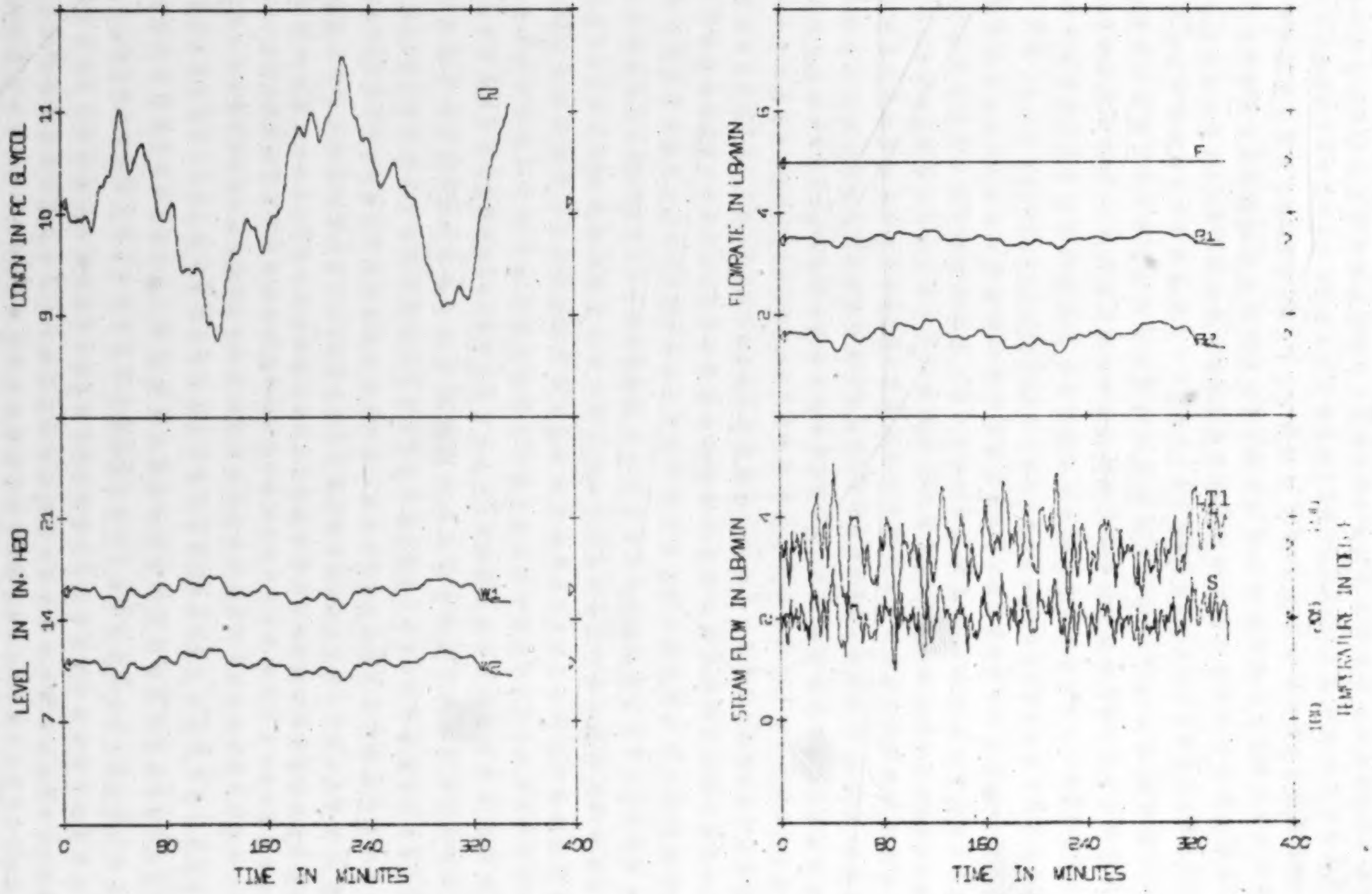


FIGURE 3.4 OPEN LOOP SIMULATION DATA FOR RUN SS-6

3.5.1 Choice of Input Signal

For model identification it is desirable to have an input signal which excites all modes of the process so that the information content of the input and output series is large and a satisfactory model can be obtained from the data. It is also desirable to have input signals that minimise the volume of the joint confidence interval of the parameter estimates (i.e. D-optimal signals). This objective may require very large input variations which are not always possible in practice. For cases where the input variance is constrained, Hong and McGregor [5] have suggested the use of first order autoregressive input sequences with positive parameters (i.e. $\phi > 0$).

In three runs, SS-4 to SS-6, the standard deviation of steam, σ_S, is fairly constant so the effect of the autoregressive parameter ϕ on the output standard deviation σ_{C2}, can be evaluated. Table 3.1 indicates that σ_{C2} increases sharply as the autoregressive parameter ϕ increases and σ_S remains almost constant. For a value of $\phi = 0.5$, the σ_{C2} value is almost twice as large as the value for the $\phi = 0$ (or white noise) case. Similarly, for $\phi = 0.75$ the standard deviation is three times that of the run with $\phi = 0$. From Table 3.3 it is clear that for autoregressive input signals, the confidence limits on the parameter estimates become smaller as ϕ increases indicating more confidence in the parameter estimates.

3.5.2 Comparison with Theoretical Process Transfer Function Model

The parameter estimates and the theoretical model parameters are presented in Table 3.2. The 95 percent confidence intervals for the parameters appear in the Appendix D. It can be seen that when the assumed model orders are correct (runs SS-1 to SS-3), the autoregressive parameters $\{\hat{\delta}_j\}$ are exactly the same as those of the theoretical model but some of the moving average parameters $\{\hat{\omega}_j\}$ differ significantly ($\sim$ 20%) from the theoretical values. The time series model produces residuals with a small sum of squares of residuals but the cross correlation between prewhitened inputs and the residuals are significant, as indicated by the large values of $S_{\alpha a}$. However, the cross correlation values do not show any particular pattern. The $S_{\alpha a}$ values for runs SS-1 to SS-3 are much larger than the value of 25.0 which corresponds to the 95 percent confidence level for 15 degrees of freedom. This indicates little confidence in the models, whereas the sum of squares of residuals indicates a good fit in the least square sense.

In Table 3.2, for runs SS-1 and SS-2 the Q_a values indicate adequate noise models but since the $S_{\alpha a}$ values indicate little confidence in the process models and the noise is dependent on the corrections of the process models, noise model adequacy is of little significance.

Runs SS-4 to SS-6 with "incorrect" model orders indicate more confidence in the models as can be judged from the small $S_{\alpha a}$ values; however they produce higher sum of squares of residuals.

TABLE 3.3

EFFECT OF INPUT SIGNAL STRUCTURE ON PARAMETER ESTIMATES

(Open Loop Simulated Data, steam disturbances, level control only)

Run No.	Model	Input ϕ_S	$\hat{\delta}_1$	$\hat{\delta}_2$	$\hat{\omega}_o$	$\hat{\omega}_1$	$\hat{\phi}_1$	$\hat{\phi}_2$	$\hat{\theta}_1$	$S_{\alpha a}$	Q_a	Σa_t^2
SS-4	(2,1,1) (1,0,1)	0	1.689	-0.759	0.0096	-0.0043	0.918	-	0.207	8.67	47.6*	0.338
			1.779	-0.678	0.0318	0.0178	1.011	-	0.333			
			1.598	-0.840	-0.0125	-0.0265	0.825		0.062			
SS-5	(2,1,1) (2,0,1)	0.75	1.548	-0.559	0.0103	-0.0156	-0.0535	0.530	-0.535	12.99	28.66	0.0608
			1.648	-0.557	0.0223	-0.0032	0.0200	0.6205	-0.428			
			1.547	-0.561	-0.0017	-0.0281	-0.127	0.4390	-0.642			
SS-6	(2,1,1) (2,0,1)	0.50	1.628	-0.638	0.0148	0.0066	- .318	0.175	-0.474	11.25	34.34*	1.36
			1.628	-0.636	0.0249	0.0039	-0.275	0.2891	-0.349			
			1.628	-0.639	0.0048	0.0171	-0.361	0.0605	-0.589			

* values of $S_{\alpha a}$ or Q_a larger than $\chi^2_{0.05}$

3.5.3 Models from Open Loop Simulation Data

In the simulation runs of Tables 3.1 and 3.2 where only the steam is disturbed, the residuals represented modelling errors. In order to have a more meaningful noise term, the feed flow rate was also perturbed in a random fashion which produced deviations in the output variable that were not related to the input (steam) signal. The extent of change in model orders and parameter estimates in presence of feed flow perturbations was studied by comparing runs SSF-1 to SSF-4 in Table 3.4 with runs SS-4 to SS-6 where feed disturbances were absent.

Figure 3.7a presents a typical plot of cross correlations between prewhitened input and transformed output for run SSF-2. Up to lag zero there are no significant cross correlations indicating a dead time of one sampling interval. From lag $k = 1$ onwards, the cross correlations increase gradually and are almost constant between $k = 8$ to $k = 15$. It was difficult to analyse this plot to get initial model orders. Consequently knowledge of the theoretical evaporator model indicated that model orders of $(r, s, b) \equiv (2, 1, 1)$ would be reasonable. The initial parameter estimates thus obtained were used to calculate initial estimates of N_t. The values of auto and partial auto correlations of ∇N_t indicated a mixed first order autoregressive-moving average model. All of the initial parameter estimates were used in the nonlinear, recursive, least squares, estimation program to calculate the final parameter estimates. Figure 3.7b, c and d show the cross correlation, auto and partial auto correlations of the residual series. No systematic patterns are apparent but there are one or two correlation values that

TABLE 3.4

CONDITIONS FOR OPEN LOOP SIMULATION RUNS

(Steam and feed flow disturbances, level control only)

Run No	Steam (lb/min)			Feed (lb/min)			Concentration (% glycol)
	σ input	ϕ_S	σ_S	σ input	ϕ_F	σ_F	σ_{C2}
SSF-1	0.30	0.50	0.340	0.50	0	0.485	0.65
SSF-2	0.30	0.75	0.435	0.50	0.50	0.530	1.27
SSF-3	0.40	0.50	0.447	0.50	0.75	0.675	1.12
SSF-4	0.20	0.50	0.227	0.75	0.75	1.010	1.27

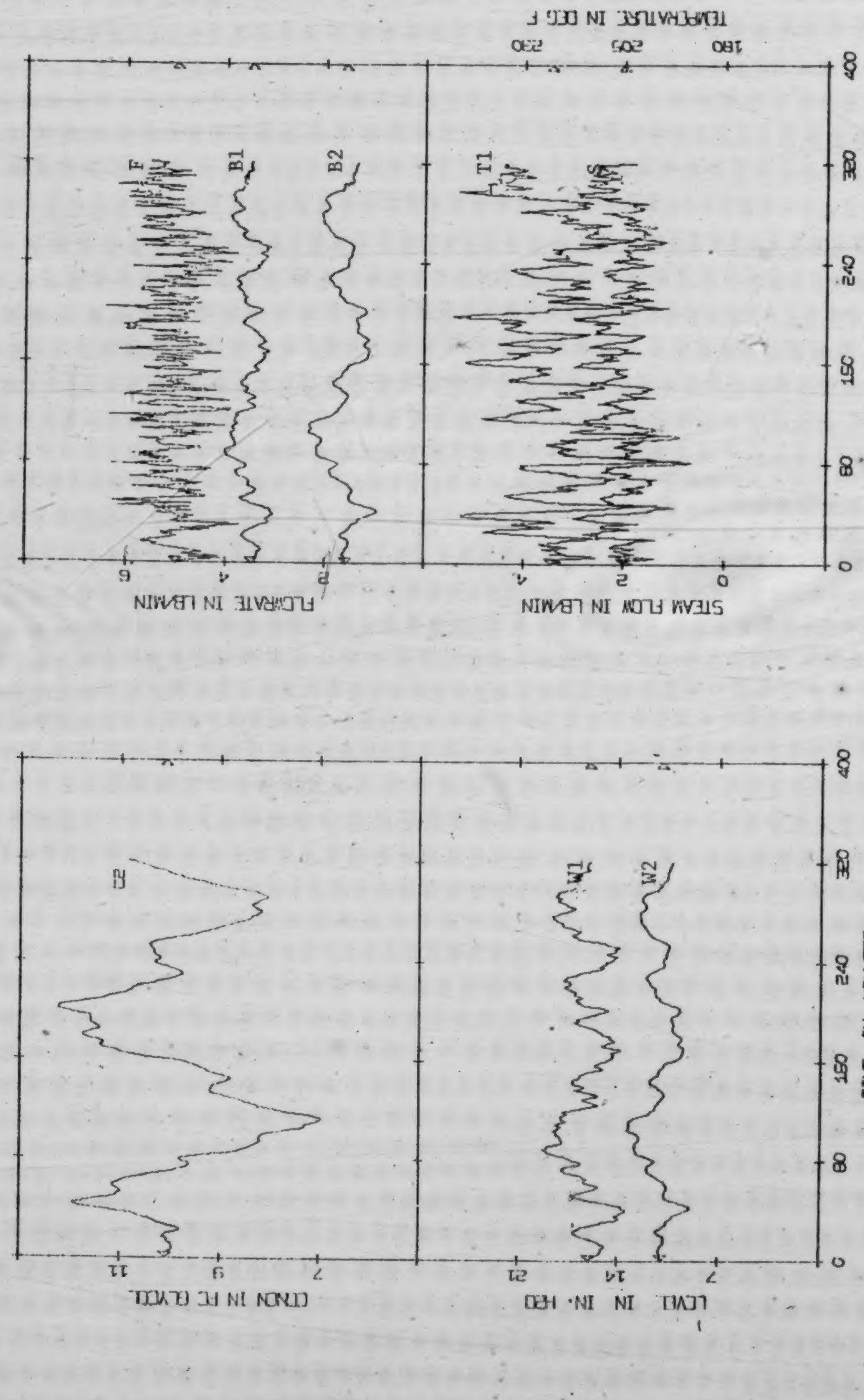


FIGURE 3.5 OPEN LOOP SIMULATION DATA FOR RUN SSF-1

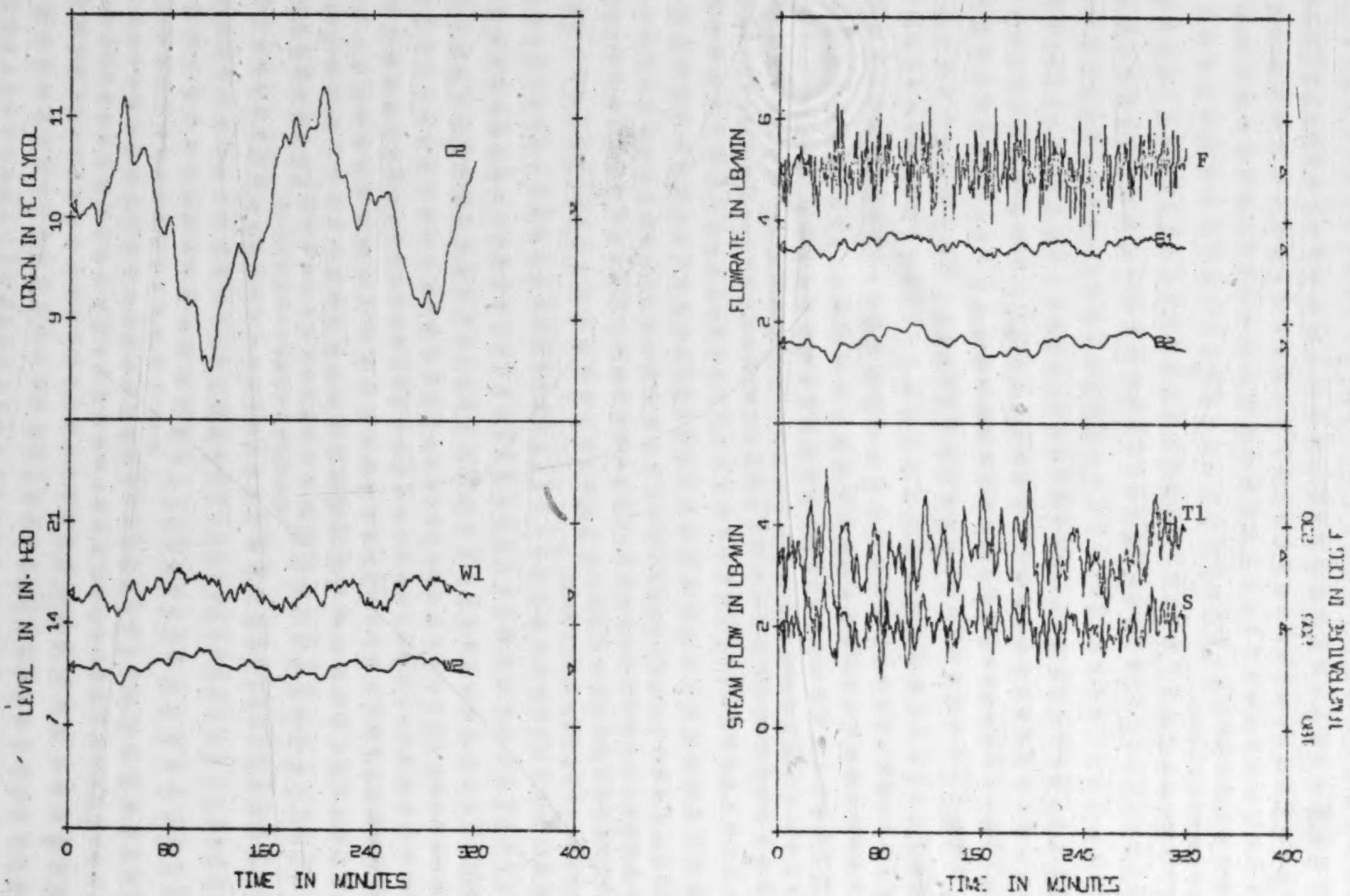
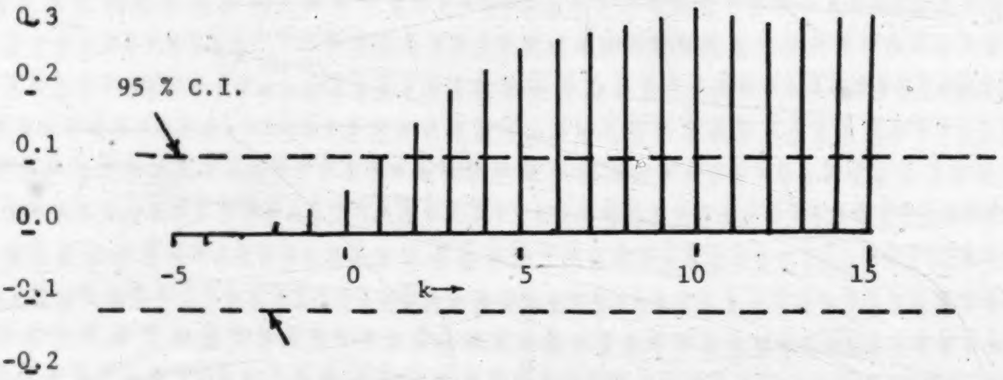
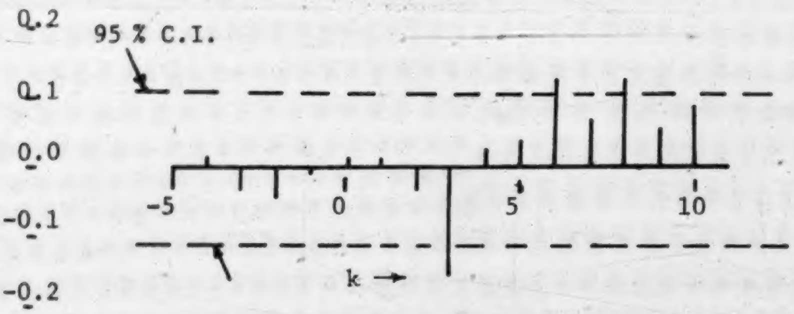


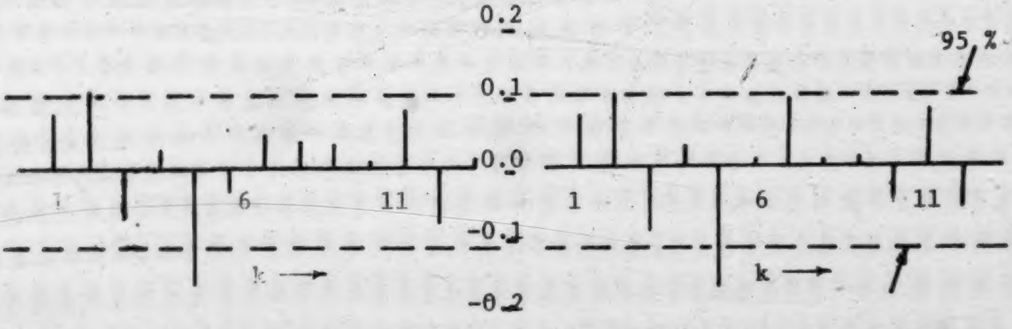
FIGURE 3.6 OPEN LOOP SIMULATION DATA FOR RUN SSF-2



a. Cross correlation function, $\rho_{\alpha\beta}(k)$



b. Cross correlation function of residuals, $\rho_{\alpha a}(k)$



c. Autocorrelation function of residuals, $\gamma_a(k)$

d. Partial autocorrelation function of residuals, $\phi_a(k)$

FIGURE 3.7 CORRELATIONS FOR SIMULATION RUN SSF-2

lie outside the 95 percent confidence limits. In Table 3.5 the value of $S_{\alpha a}(17) = 28.87$ for run SSF-2 indicates that the model is within the 96 percent confidence limits and similarly the value of $Q_a(18) = 30.08$ also indicates 96 percent confidence limits.

For runs both with and without feed flow disturbances (i.e. runs SS-4 to SS-6 and SSF-1 to SSF-4) the process transfer function models with model orders $(r, s, b) \equiv (2, 1, 1)$ were found to be adequate. The $S_{\alpha a}$ values for these models were generally within 95 percent confidence intervals. With an increase in the number of parameters, the fit is generally better (lower chi-square values) but at the cost of wider confidence intervals for the parameter estimates.

Physically, a (2, 1, 1) model has a dead time of one sampling interval and means that the current product concentration depends on two past values of steam flow and two past values of product concentration:

$$Y_t = \delta_1 Y_{t-1} + \delta_2 Y_{t-2} + \omega_o X_{t-1} - \omega_1 X_{t-2} + N_t - \delta_1 N_{t-1} - \delta_2 N_{t-2} \qquad (3.8)$$

where

Y_t = normalized deviation of product concentration from steady state value at time t;

X_t = normalized deviation of steam flow rate from steady state value at time t;

$\delta_1, \delta_2, \omega_o, \omega_1$ are constants;

N_t = noise at time t.

Table 3.6 presents the parameter estimates for run SSF-3 assuming different model orders. For different noise models the transfer function model parameters $\{\hat{\delta}_i\}$ are also different. For example, for the second order autoregressive noise models $\hat{\delta}_1$ changes from 1.509 to 1.44 and $\hat{\delta}_2$ changes from -0.51 to -0.47. On the other hand the $\{\hat{\omega}_o\}$ are fairly close (within 2 percent of each other) except for the runs where no noise models were fitted. The variations in parameters indicate their sensitivity to the assumed noise model orders.

The (2, 1, 0) noise model is considered to be the best model for this run because it provides small values of chi-square statistics (S and Q), (both S and Q are within 95 percent confidence intervals) and has one less parameter than the (2, 1, 1) noise model which produces slightly smaller chi-square values for the auto and cross correlations. Other noise models are inadequate because they produce high values of Q. For other runs the parameter estimates using different noise models and also their confidence intervals are presented in Appendix D.

Runs SSF-3(F) to SSF-3(H) illustrate the effect of assuming different process models. For run SSF-3(F), the order of s is increased from 1 to 2 and the $\{\tilde{\delta}_j\}$ are close to those for run SSF-3(A) but the $\{\hat{\omega}_j\}$ are completely different. Similarly, for runs SSF-3(G) and SSF-3(H) the $\{\hat{\delta}_j\}$ are close although they are quite different from all other runs. For these runs, two of the three roots of the polynomial, $\hat{\delta}(B)$, are approximately equal to those of run SSF-3(A) but this is not the case for $\{\hat{\omega}(B)\}$. It

TABLE 3.5

PARAMETER ESTIMATES FROM OPEN LOOP SIMULATION DATA

(Steam and feed flow disturbances, Level control only)

Run No	Model	$\hat{\delta}_1$	$\hat{\delta}_2$	$\hat{\omega}_0$	$\hat{\omega}_1$	$\hat{\phi}_1$	$\hat{\phi}_2$	$\hat{\theta}_1$	$S_{\alpha a}$	Q_a	$\hat{\sigma}_a^2 \times 10^3$
SSF-1	(2,1,1) (1,1,1)	1.510	-0.515	0.0136	-0.00961	0.870	--	-0.181	28.77	23.53	0.132
SSF-2	(2,1,1) (1,1,1)	1.509	-0.514	0.0135	-0.00918	0.943	--	-0.476	28.87	30.08*	0.171
SSF-3	(2,1,1) (2,1,0)	1.444	-0.472	0.0128	-0.00992	1.649	-0.686	--	22.97	25.77	0.155
SSF-4	(2,1,1) (2,1,0)	1.366	-0.469	0.0122	-0.00987	1.657	-0.695	--	26.78	25.27	0.298

* Values of $S_{\alpha a}$ or Q_a larger than $\chi^2_{0.05}$

TABLE 3.6

EFFECT OF ASSUMING DIFFERENT MODEL ORDERS ON PARAMETER ESTIMATES

(Simulated data for open loop run SSF-3, steam and feed disturbances, level control only).

Run No.	Model	$\hat{\delta}_1$	$\hat{\delta}_2$	$\hat{\delta}_3$	$\hat{\omega}_o$	$\hat{\omega}_1$	$\hat{\omega}_2$	$\hat{\phi}_1$	$\hat{\phi}_2$	$\hat{\theta}_o$	$S_{\alpha a}$	Q_a	Σa_t^2
SSF-3(A)	(2,1,1) (0,0,0)	1.509	-0.516	-	0.0206	-0.0032	-	-	-	-	2.46	-	1.23
SSF-3(B)	(2,1,1) (1,1,0)	1.509	-0.515	-	0.0137	-0.0098	-	0.982	-	-	24.00	179.14*	2.67×10^{-4}
SSF-3(C)	(2,1,1) (2,1,0)	1.444	-0.412	-	0.0128	-0.0099	-	1.649	-0.686	-	22.97	25.77	1.58×10^{-4}
SSF-3(D)	(2,1,1) (1,1,1)	1.509	-0.513	-	0.0136	-0.0101	-	-0.970	-	-0.597	26.27	50.57*	1.69×10^{-4}
SSF-3(E)	(2,1,1) (2,1,1)	1.440	-0.465	-	0.0129	-0.0100	-	1.496	-0.536	-0.268	21.79	22.55	1.55×10^{-4}
SSF-3(F)	(2,2,1) (0,0,0)	1.509	-0.517	-	0.0084	-0.0545	0.022	-	-	-	5.75	-	12.1×10^{-4}
SSF-3(G)	(3,1,1) (0,0,0)	2.313	-1.709	0.342	0.0254	0.0227	-	-	-	-	-**	-	-
SSF-3(H)	(3,2,1) (0,0,0)	2.306	-1.709	0.342	0.0083	0.0235	0.0081	-	-	-	-**	-	-

* Values of $S_{\alpha a}$ or Q_a larger than $\chi^2_{0.05}$

* S, Q, Σ_{at}^2 not calculated due to program overflow.

can be seen that the process can be adequately described with a lower order model as the lower order model also satisfies the chi-square criteria.

By comparing runs SS-4 to SS-6 (Table 3.2) and runs SSF-1 to SSF-3 (Table 3.5) it can be observed that the autoregressive model parameter estimates, $\{\hat{\delta}_j\}$, decrease by up to 20 percent when feed disturbances are introduced, while the moving average parameter estimates, $\{\hat{\omega}_j\}$, are fairly close. In run SSF-4 where the feed disturbance magnitude is twice as large as the steam flow disturbance, the $\{\hat{\delta}_j\}$ decrease even further. Thus it seems that as σ_F/σ_S increases, the $\{\hat{\delta}_j\}$ decrease but the $\{\hat{\omega}_j\}$ remain fairly constant.

Looking at the noise models, one sees that the N_t series is stationary when feed disturbances are absent and the fitted noise models have order of the differencing (d) equal to zero. But in the presence of feed flow disturbances they exhibit nonstationary behaviour and differencing the residual series $\hat{N}_t$ once produces a stationary series. As expected, the noise models and parameters are completely different for these two types of disturbances.

For runs SSF-1 and SSF-2 the noise models have the same orders and the autoregressive parameters are close. The values of moving average parameter $\hat{\theta}_1$ have the same signs and are comparable in magnitude. For runs SSF-3 and SSF-4 where the input series structures are similar (ϕ_S and ϕ_F constant), the noise models have the same structure and the parameter estimates closely agree.

3.6 Identification using Open Loop Experimental Data

As in the simulation study two sets of experimental runs were carried out: the first set with steam disturbances only, and the second set with additional feed flow disturbances. Tables 3.7 and 3.8 summarize the run conditions and typical runs are presented in Figs. 3.8 to 3.12.

In each set of runs, proportional level control was employed. Runs S-1 to S-4 and SF-1 to SF-4, used controller matrix $\underset{\approx}{K}_1$ in eqn. (3.7) which was also used in the simulation study. For run SF-5 a different controller matrix, $\underset{\approx}{K}_2$, was used:

$$\underset{\approx}{K}_2 = \begin{bmatrix} 1.5 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 6.5 & 0 \end{bmatrix} \qquad (3.9)$$

In the experimental runs 400 data points were collected at 64 second intervals. For the model identification 320 points beginning at the 29th data point were used. The first 28 points were not considered in order to eliminate the effect of the initial transient caused when disturbances suddenly began.

The steam perturbations were introduced by changing the set point of the steam flow control loop every sampling instant. Similarly the total feed flow rate was changed by changing the set points of the feed water and feed solution control loops, so as to maintain constant feed concentration.

Comparison of C2 responses using the simulations (Figs. 3.2 to 3.6) and experiments (Figs. 3.8 to 3.12)indicates that unlike the simulated responses, experimental responses exhibit time variant means or decaying or growing oscillations, indicating different types of process noise.

TABLE 3.7

CONDITIONS FOR OPEN LOOP EXPERIMENTS

(Steam flow disturbances, level control[1] only)

Run No	Steam (lb/min)			Concentration (% glycol)	
	σ_{input}	ϕ_S	σ_S	σ_{C2}	C2(0)*
S-1	0.25	0	0.251	0.32	10.0
S-2	0.25	0.50	0.335	0.50	9.3
S-3	0.25	0	0.317	0.44	9.2
S-4	0.20	0.75	0.387	0.71	9.5

* C2(0) is the initial steady state glycol concentration.

[1] Control matrix $\underline{\underline{K}}_1$ in eqn. 3.7 was used.

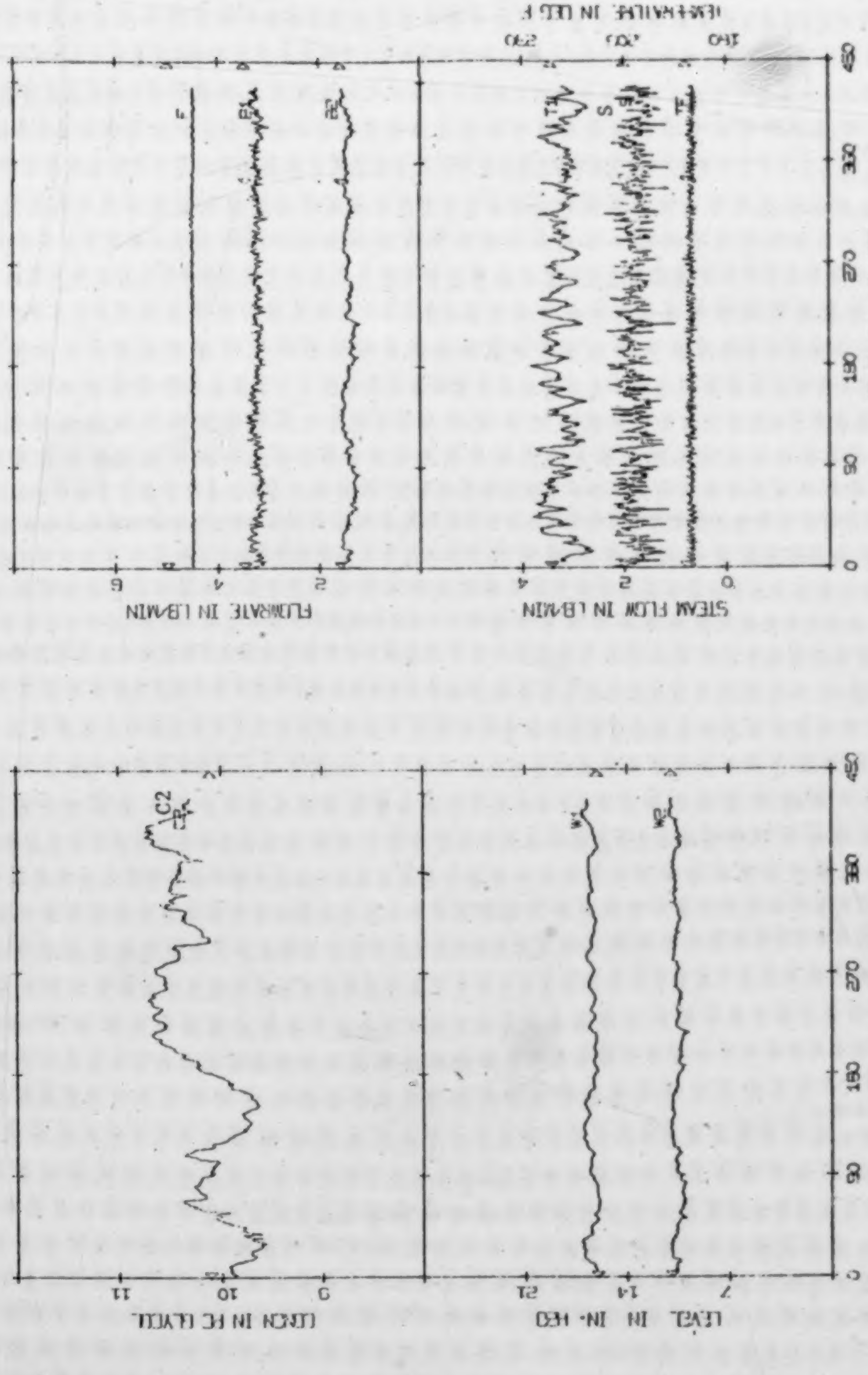


FIGURE 3:8 OPEN LOOP EXPERIMENTAL DATA FOR RUN S-1

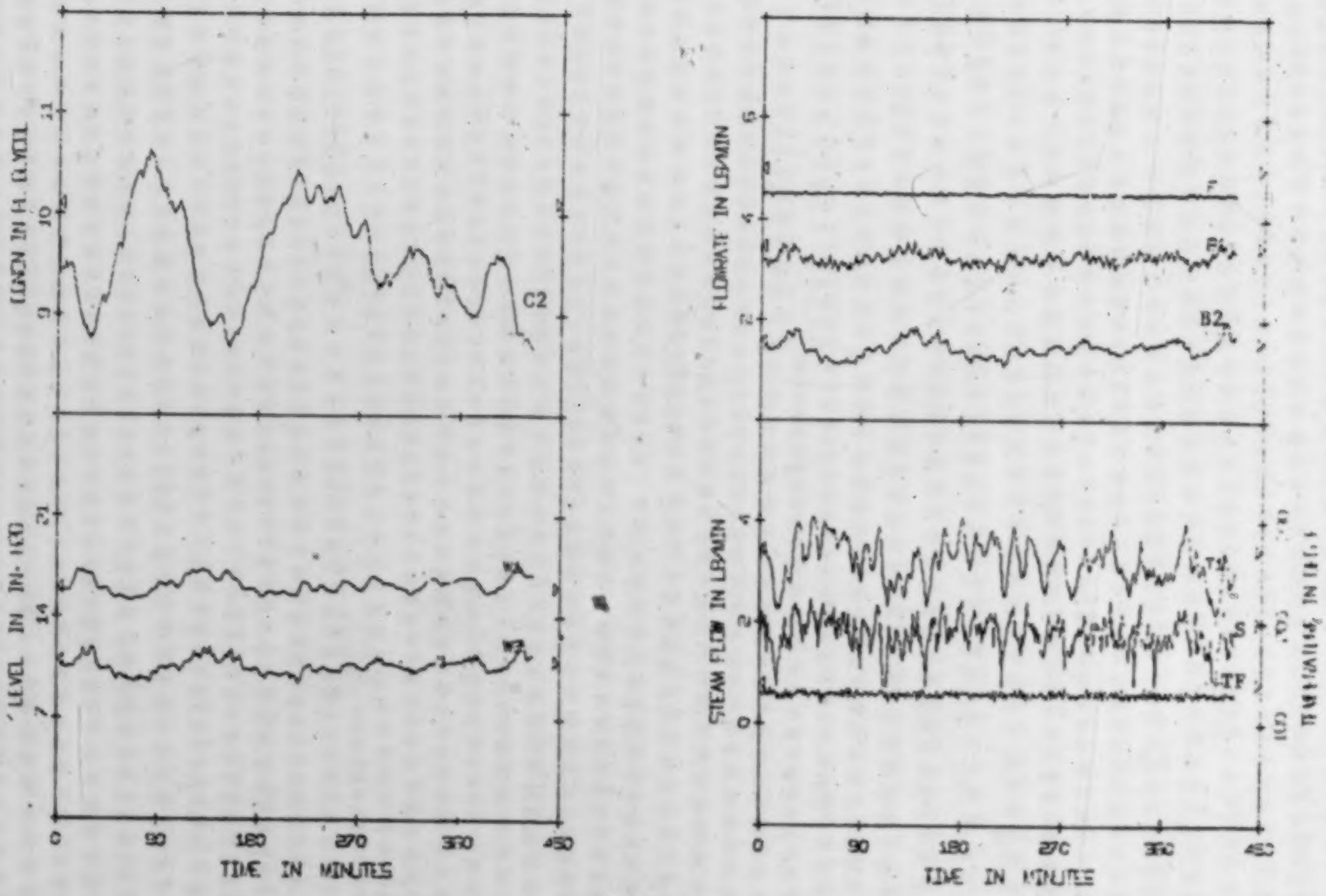


FIGURE 3.9 OPEN LOOP EXPERIMENTAL DATA FOR RUN S-2

TABLE 3.8

CONDITIONS FOR OPEN LOOP EXPERIMENTS

(Steam and feed flow disturbances, level control only)

Run No	Steam (lb/min)			Feed (lb/min)			Concentration (%glycol)	
	σ_{input}	ϕ_S	σ_S	σ_{input}	ϕ_F	σ_F	σ_{C2}	C2(0)
SF-1	0.10	0.75	0.164	0.15	0	0.147	0.36	9.4
SF-2	0.125	0.50	0.148	0.15	0	0.149	0.34	10.1
SF-3	0.125	0.75	0.206	0.075	0.5	0.087	0.53	10.7
SF-4	0.125	0.75	0.196	0.075	0.5	0.087	0.52	9.4
SF-5*	0.125	0.75	0.220	0.20	0.75	0.227	0.62	10.0

* control matrix $\underline{\underline{K}}_2$ in eqn. 3.9 was used for Run SF-5.
for all other Runs matrix $\underline{\underline{K}}_1$ was used.

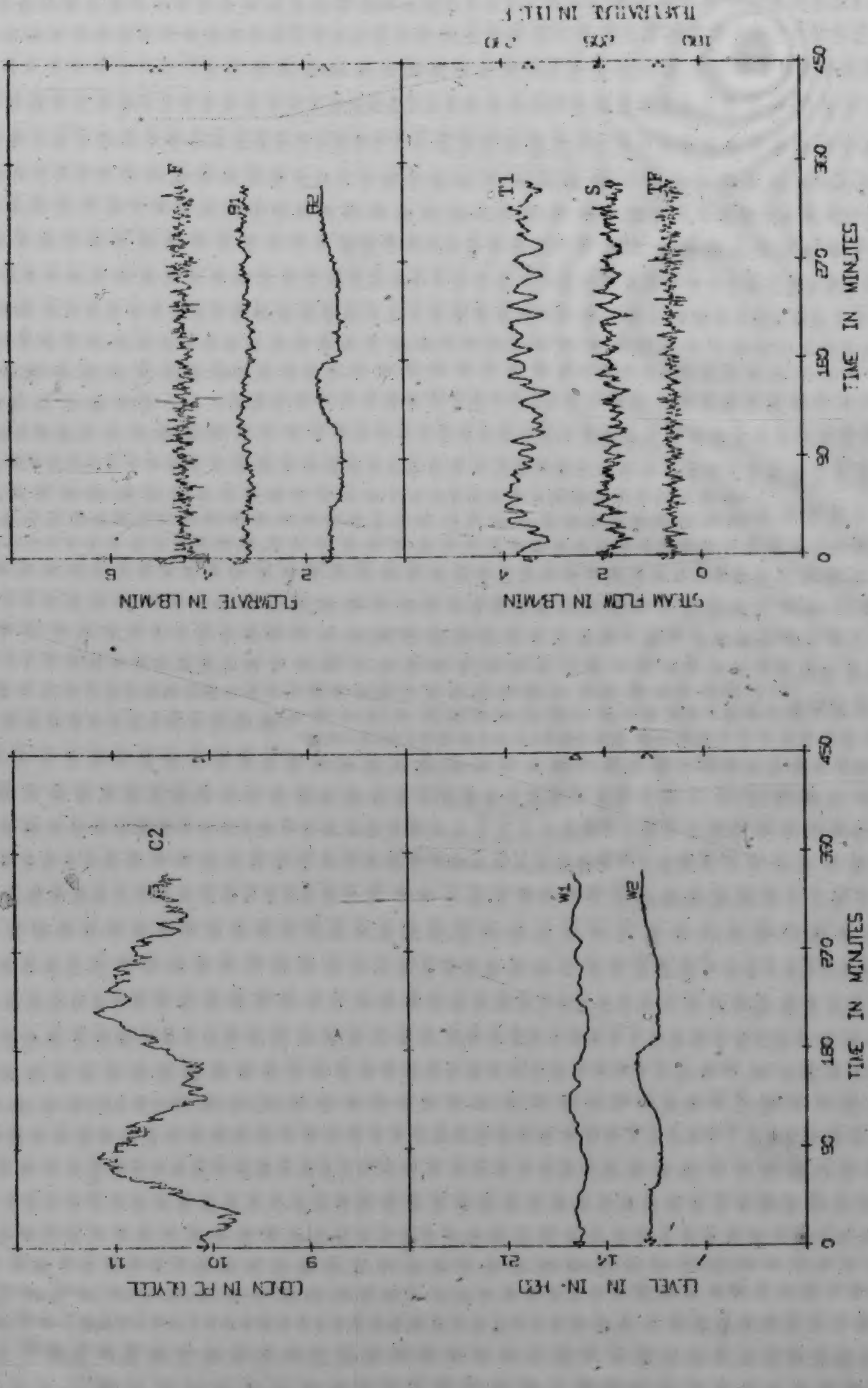


FIGURE 3.10 OPEN LOOP EXPERIMENTAL DATA FOR RUN SF-2

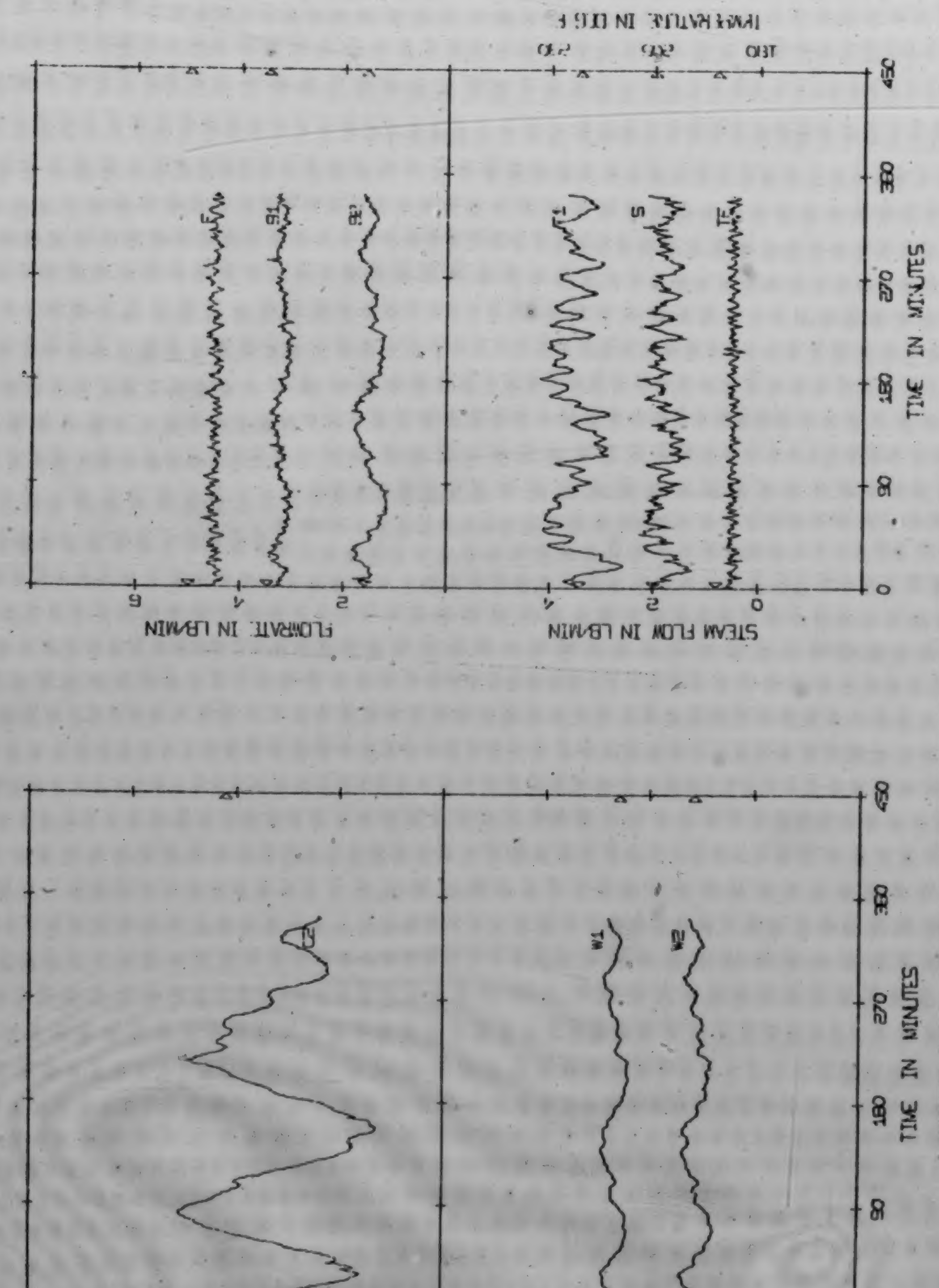


FIGURE 3.11 OPEN LOOP EXPERIMENTAL DATA FOR RUN SF-4

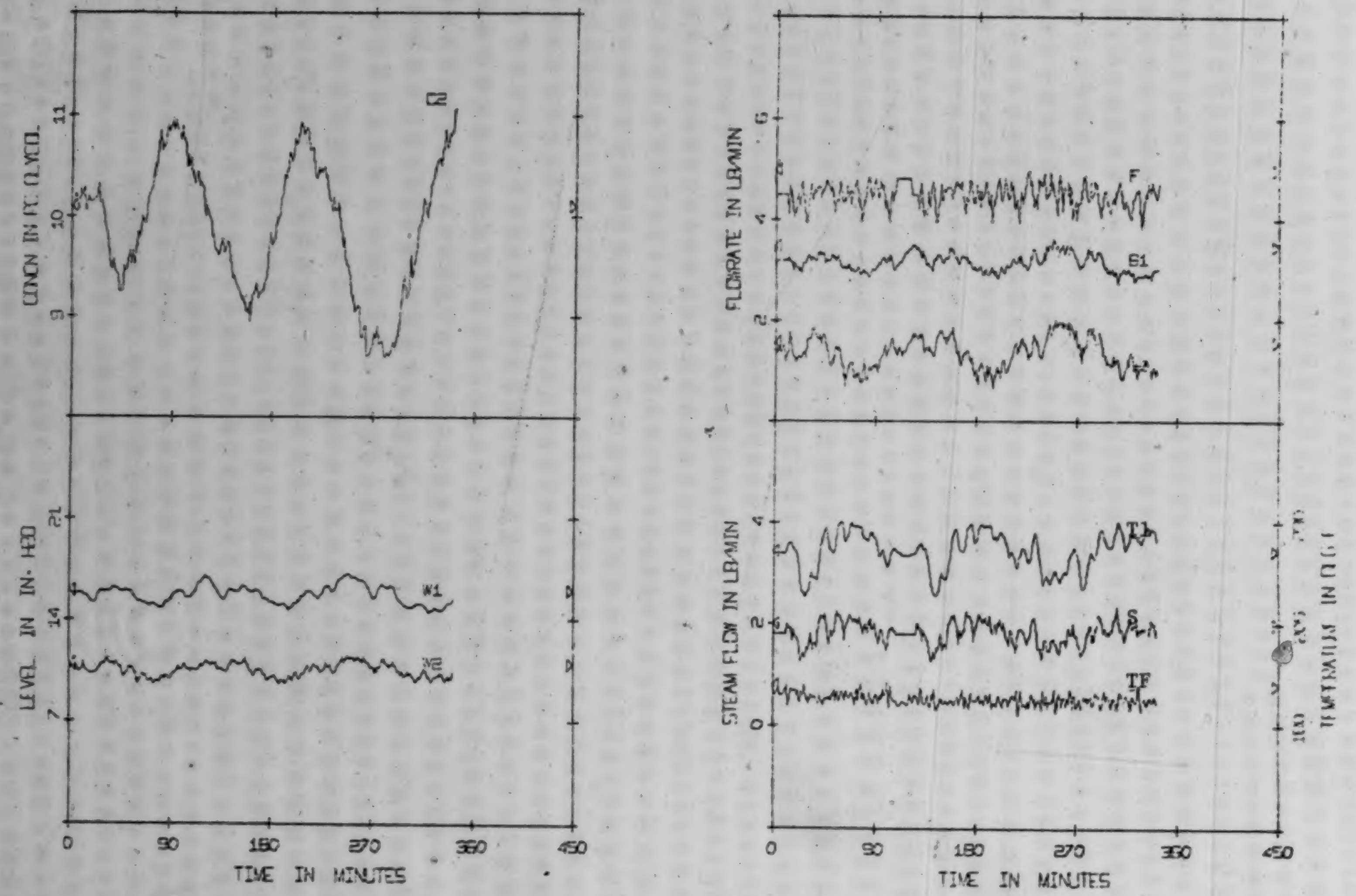


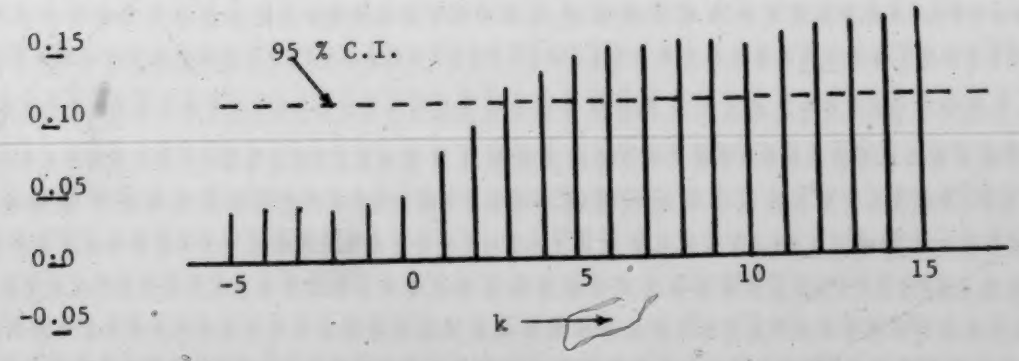
FIGURE 3.12 OPEN LOOP EXPERIMENTAL DATA FOR RUN SF-5

3.6.1 Process Models from Open Loop Experiments

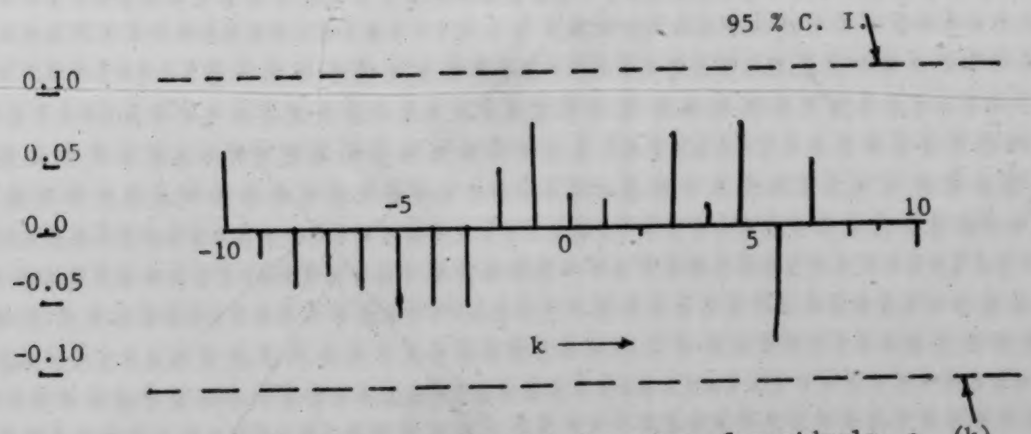
Figure 3.13a presents the plot of cross correlations between input and output for experimental run S-3. Up to lag zero the cross correlation values are well within the 95 percent confidence intervals and are almost equal in magnitude. At lag $k = 1$ the cross correlation value increases from 0.047 to 0.077. This suggests a transfer function model with $b = 1$.

As in the case of the simulation data in Fig. 3.7a, the cross correlation values gradually increase from lag $k = 1$ to $k = 6$ and are fairly constant thereafter. Previous knowledge of the theoretical evaporator model was used to determine initial model orders of $(r, s, b) \equiv (2, 1, 1)$. The estimated noise series N_t, was calculated using the initial parameter estimates. The auto and partial autocorrelations of $\hat{N}_t$ indicated a second order autoregressive structure. After some trial and error, a better fitting ARMA noise model with orders $(p, d, q) \equiv (2, 0, 1)$ was obtained. The cross, auto and partial autocorrelations of the residual series, a_t, are plotted in Fig. 3.13b, c and d. All the correlation values are well within the 95 percent confidence limits and no systematic patterns are evident. The $S_{\alpha a}$ value of 12.99 (from Table 3.9) indicates transfer function model adequacy. Similarly, $Q_a(17) = 15.85$ indicates noise model adequacy using the chi-square test.

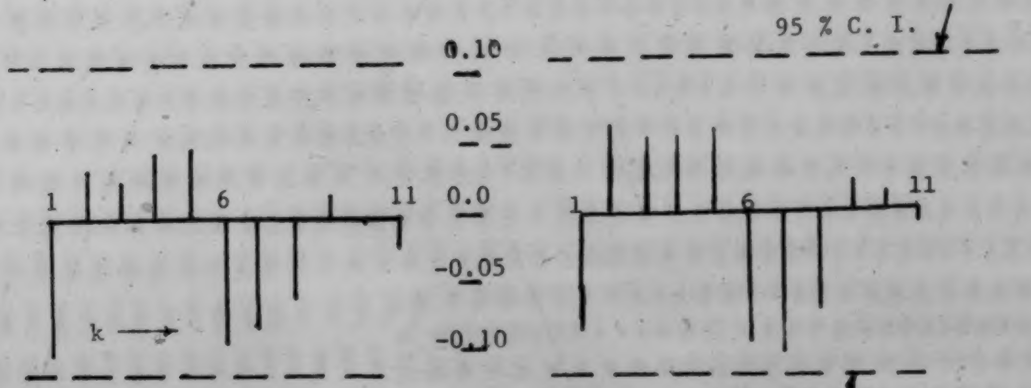
Table 3.9 presents the effect of assuming different model orders (process and noise) on the parameter estimates for a typical open loop experimental run, S-1. Runs A-D illustrate the effect of



a. Cross correlation function, $\rho_{\alpha\beta}(k)$



b. Cross correlation function of residuals, $\rho_{\alpha a}(k)$



c. Autocorrelation function of residuals, $\gamma_a(k)$

d. Partial autocorrelation function of residuals, $\phi_a(k)$

FIGURE 3.13 CORRELATIONS FOR EXPERIMENTAL RUN S-3

TABLE 3.9

EFFECT OF ASSUMING DIFFERENT MODEL ORDERS ON PARAMETER ESTIMATES

(Experimental data for open loop run S-1, steam disturbances, level control only)

Run No.	Model	$\hat{\delta}_1$	$\hat{\delta}_2$	$\hat{\delta}_3$	$\hat{\omega}_0 \times 10^2$	$\hat{\omega}_1 \times 10^3$	$\hat{\omega}_2 \times 10^3$	ϕ_1	ϕ_2	θ_1	$S_{\alpha a}$	Q_a	$\Sigma a_t^2 \times 10^2$
A	(2,1,1) (2,0,0)	1.700	-0.703	-	0.940	-0.486	-	0.884	0.101	-	17.22	38.19*	0.431
B	(2,1,1) (2,1,0)	1.700	-0.704	-	0.826	-1.26	-	0.117	-0.133	-	18.84	32.61*	0.439
C	(2,1,1) (2,0,1)	1.700	-0.703	-	0.999	0.248	-	1.013	-0.246	0.134	16.88	37.61*	0.436
D	(2,1,1) (1,1,0)	1.700	-0.703	-	0.938	-0.551	-	-0.107	-	-	17.62	39.60*	0.434
E	(2,1,1) (0,0,0)	1.700	-0.703	-	0.570	1.613	-	-	-	-	17.65	-	17.3
F	(2,2,1) (0,0,0)	1.700	-0.702	-	2.72	16.39	0.341	-	-	-	21.74	-	16.0
G	(3,2,1) (0,0,0)	1.700	-0.700	-0.0024	0.609	- 1.743	0.518	-	-	-	9.36	-	14.5
H	(3,1,1) (0,0,0)	1.700	-0.697	-0.0050	0.471	- 3.231	-	-	-	-	5.72	-	15.3
I	(3,1,1) (1,0,1)	1.698	-0.825	0.1137	1.275	1.647	-	0.947	-	0.002	24.09	75.92*	0.547
J	(3,1,1) (1,0,0)	1.665	-0.906	0.293	0.942	- 1.390	-	0.978	-	-	36.14*	43.43*	0.507

* Values of $S_{\alpha a}$ or Q_a larger than $\chi^2_{0.05}$

assuming different noise models. Here a change in the noise model has almost no effect on the autoregressive parameters estimates $\{\hat{\delta}_j\}$. On the other hand, variations in $\hat{\omega}_o$ are up to 10 percent and $\hat{\omega}_1$ exhibits very large fluctuations in value from -1.26×10^{-3} to 0.25×10^{-3}. For different noise models, the noise model parameter estimates have widely varying values but the sum of squares of residuals undergoes little change. For runs A-D all $S_{\alpha a}$ values are smaller than chi-square value of 27.6, thus showing transfer function model adequacy. All the Q_a values indicate confidence limits wider than 95 percent.

Runs E-H show the effect of using different transfer function models. Here the runs have autoregressive parameter estimates that are close to the estimates in runs A-D; however the $\{\hat{\omega}_j\}$ are quite different. These runs indicate that with more parameters (higher orders), the sum of squares of residuals is smaller and also smaller $S_{\alpha a}$ are obtained. The use of a noise model greatly reduces the sum of squares of residuals.

For open loop runs S-1 to S-4 and SF-1 to SF-5, the models which provided the best fit are presented in Tables 3.10 and 3.11. Additional models and the confidence limits for the parameters are presented in Appendix D. It can be seen that for runs using the level control matrix $\underline{\underline{K}}_1$, the $\{\hat{\delta}_i\}$ have remained unchanged with the exception of run SF-2. For run SF-5 using tighter control on levels (i.e. control matrix $\underline{\underline{K}}_2$ in eqn. (3.9)), the $\{\hat{\delta}_i\}$ are smaller with one of the roots of $\hat{\delta}(B)$ moving away from the unit circle, but having little effect on the other root.

TABLE 3.10

PARAMETER ESTIMATES FOR OPEN LOOP EXPERIMENTS

(Steam flow disturbances, Level control[1] only)

Run No	Model	$\hat{\delta}_1$	$\hat{\delta}_2$	$\hat{\omega}_0$ $\times 10^2$	$\hat{\omega}_1$ $\times 10^2$	$\hat{\phi}_1$	$\hat{\phi}_2$	$\hat{\theta}_1$	$S_{\alpha a}$	Q_a	Σa_t^2 $\times 10^2$
S-1	(2,1,1) (2,1,0)	1.700	-0.704	0.826	-0.126	-0.117	-0.133	--	18.84	32.61*	0.43
S-2	(2,1,1) (1,1,0)	1.700	-0.704	0.774	-0.114	-0.097	--	--	24.09	11.76	0.33
S-3	(2,1,1) (2,0,1)	1.699	-0.710	0.691	0.058	1.918	-0.922	0.735	12.99	15.85	0.15
S-4	(2,1,1) (1,1,0)	1.700	-0.706	0.612	-0.194	-0.192	--	--	20.55	20.33	1.04

[1] Control matrix $\underline{\underline{K}}_1$ in eqn. 3.7 was used.

* Value of Q_a larger than $\chi^2_{0.05}$

TABLE 3.11

PROCESS MODELS FROM OPEN LOOP EXPERIMENTS

(Steam and feed flow disturbances, level control only)

Run No.	Model	$\hat{\delta}_1$	$\hat{\delta}_2$	$\hat{\omega}_o \times 10^2$	$\hat{\omega}_1 \times 10^2$	$\hat{\phi}_1$	$\hat{\phi}_2$	$\hat{\theta}_1$	S_{aa}	Q_a	$\Sigma a_t^2 \times 10^2$
SF-1	(2,1,1) (1,1,0)	1.700	-0.700	1.185	0.222	-0.221	-	-	14.80	23.90	0.79
SF-2	(2,1,1) (1,1,1)	1.804	-0.915	-0.162	-0.406	0.158	-	0.338	41.15*	23.23	2.23
SF-3	(2,1,1) (1,1,0)	1.700	-0.705	0.932	-0.209	-0.226	-	-	15.95	73.75*	0.11
SF-4	(2,1,1) (1,1,1)	1.700	-0.705	0.957	-0.162	0.557	-	0.649	25.44	37.77*	0.23
SF-5**	(2,1,1) (2,1,1)	1.510	-0.518	1.184	-0.182	-0.0945	-0.112	0.202	17.24	28.15	2.05

* Values of S_{aa} or Q_a larger than $\chi^2_{0.05}$

** Control Matrix $\underline{K}_2$ in eqn. (3.9) was employed for Run SF-5

All other runs used $\underline{K}_1$ eqn. (3.7)

In the numerator polynomial, $\hat{\omega}(B)$, $\hat{\omega}_o$ has various values between 0.61×10^{-2} to 1.185×10^{-2} for both sets except for run SF-2 where it is -0.162×10^{-2}. The value of $\hat{\omega}_1$ has increased by an order of magnitude for the case of simultaneous steam and feed disturbances. With the tighter level control in run SF-5 the value of $\hat{\omega}_1$ further increases. Within one set of runs the value of $\hat{\omega}_1$ exhibits large variations but the order of magnitude remains unchanged. This indicates sensitivity of $\{\hat{\omega}_j\}$ to changes in process conditions. However the autoregressive polynomial, $\delta(B)$ is sensitive only to the level control matrix.

The residual noise sequence, N_t, was generally nonstationary, requiring one degree of differencing to get a stationary series. The noise models for all but one of the runs were dominated by first order autoregressive structures after differencing once. For run S-3 the noise was best described by a second order autoregressive and first order moving average model (model orders (2, 0, 1)). In runs SF-2 and SF-4 after differencing once a mixed autoregressive moving average noise was observed.

For the runs with noise model (1, 1, 0), the autoregressive parameter $\hat{\phi}_1$ varied between -0.0968 to -0.226. Other models have a positive moving average parameter $\hat{\theta}_1$, with widely varying magnitudes. From this it seem indicated that noise models and their parameters are sensitive to changes in process conditions.

The criteria used in selecting the best fitting noise model was as follows: When two noise models produced nearly equal S and Q values, the model having nonzero order of differencing $(d \neq 0)$ was chosen, since the control action of the minimum mean square error controller based on such noise model incorporates integral action. The next criterion was to choose a model having the least number of parameters from two or more equally adequate models.

Comparison of models obtained using experimental and simulation data shows that the same transfer function model orders adequately fit both types of data. The $\{\hat{\delta}_j\}$ obtain experimentally are 10 - 15 percent higher than for simulations, whereas the $\{\hat{\omega}_j\}$ are higher in the case of models obtained from simulation study. The increase in $\hat{\omega}_o$ and $\hat{\omega}_1$ are not proportional. The autoregressive parameter estimates, $\{\hat{\delta}_j\}$, in the case of the simulation change with change in magnitude of feed disturbances, whereas they seem to be independent of feed disturbance magnitude in the case of models based on experimental data.

No significant difference is observed between noise model orders fitted for experimental and simulation data. Similar $S_{\alpha a}$ and Q_a were obtained in the experimental and simulation data except in cases of simulation with steam disturbances only, they were higher.

3.6.2 Effect of Run Length on the Parameter Estimates

In order to study the effect of run length on the parameter estimates, various subsets of data points from run SF-4 were used. The results of parameter estimation using process model order (2, 1, 1) (0, 0, 0) are presented in Table 3.12. The first four data sets contain 120 points each starting at different sampling instants. Sets #5 - 8 were similarly chosen with 200 data points in each set. Parameter estimates from these sets are compared with those from the

TABLE 3.12

PARAMETER ESTIMATES FOR PROCESS MODEL (2,1,1) (0,0,0) USING

DIFFERENT NUMBER OF DATA POINTS FROM RUN SF-4

Set #	No. of Data pts	Time Interval Begin - End	$\hat{\delta}_1$	$\hat{\delta}_2$	$\hat{\omega}_0 \times 10^2$	$\hat{\omega}_1 \times 10^2$	$S_{\alpha a}$	95% C.I. **	$\hat{\sigma}_a \times 10^2$
1	120	1 - 120	1.732	-0.737	0.506	-0.301	22.68	0.186	0.156
2	120	36 - 155	1.902	-0.908	-2.115	-2.574	85.77*	0.186	0.136
3	120	71 - 190	1.731	-0.738	0.520	-0.572	17.31	0.186	0.084
4	120	141 - 260	1.726	-0.733	0.913	-0.465	64.33*	0.186	0.055
5	200	1 - 200	1.733	-0.741	0.452	-0.432	46.39*	0.142	0.224
6	200	36 - 235	1.724	-0.732	0.524	-0.729	55.64*	0.142	0.100
7	200	71 - 270	1.734	-0.741	0.569	-0.542	13.20	0.142	0.087
8	200	106 - 305	1.727	-0.734	0.684	-0.634	42.12*	0.142	0.067
9	320	1 - 320	1.700	-0.706	1.496	-0.398	27.61	0.112	0.141

* Values of $S_{\alpha a}$ or Q_a larger than $\chi^2_{0.05}$

** Confidence limits on auto/partial auto/cross correlations.

entire run of 320 points (Set #9).

The parameter estimates in Table 3.12 indicate that the $\{\hat{\delta}_j\}$ for the runs with 120 or 200 points are approximately 2 - 3 percent higher than the parameter estimates for the complete run. However, the estimates of ω_o for the shorter runs were lower than the estimates for total run by 50 - 75 percent. The values of ω_1 do not exhibit any particular trend, but deviate from the values for the complete run.

The differences in parameter estimates indicate that when short run lengths are used, the effects of the slower modes of the process are not fully realized and smaller values for the slower time constants are obtained.

Table 3.12 also presents the confidence intervals of the correlations for each set. A value of a cross or autocorrelation within the interval may be assumed to be equal to zero. If many correlation values lie outside these limits, this indicates model inadequacy. Runs with larger numbers of data points produce smaller confidence intervals (since the confidence interval = 2/(number of data points)$^{1/2}$) indicating more confidence in the correlation values.

In summary, it can be said that runs with large numbers of data points are more likely to take into account slower process modes and have narrower confidence intervals indicate more confidence in the estimated model. Runs with 240 to 400 data points would normally be quite adequate for the double effect evaporator.

3.7 Identification from Closed Loop Simulation Data

Process models were also identified from closed loop simulation data to evaluate the applicability of time series modelling for processes which must be maintained under closed loop control.

As per § 2.2.4 in order to obtain better estimates of the model parameters, a dither signal was added to the calculated value of the manipulated steam flow so that part of the input signal was not correlated with the output product concentration, even though feedback control was used. By treating the dither signal as an input signal, the adequacy of the identified transfer function models for the closed loop system was determined by lack of correlation between the input and the final residuals, a_t. Dither signals with different characteristics were employed and are presented in Table 3.13. Typical runs are shown in Figs. 3.14 to 3.18. As expected, the output standard deviations for disturbances and dither signal addition under closed loop are smaller than those for open loop conditions (cf. Tables 3.4 and 3.13).

With the dither signal as an input and product concentration as output, closed loop process and noise models were estimated by proceeding in the same manner as for the open loop runs. Simulations with and without additional feed flow perturbations were carried out. Runs without feed flow disturbances were performed using three different controller constants for the product concentration steam loop but using the same level controller constants. The following control matrices were used:

TABLE 3.13

CONDITIONS FOR CLOSED LOOP SIMULATION RUNS

(Steam and feed flow disturbances, product concentration and level control)

Run No.	Steam (lb /min)			Feed (lb /min)			Conc. % Glycol	Controller
	σ_{input}	ϕ_F	σ_S	σ_{input}	ϕ_F	σ_F	σ_{C2}	Matrix
SS-11	0.20	0	0.232	–	–	–	0.141	$\underline{\underline{K}}_{12}$
SS-12	0.30	0.5	0.348	–	–	–	0.202	$\underline{\underline{K}}_{12}$
SS-13	0.30	0	0.296	–	–	–	0.183	$\underline{\underline{K}}_{12}$
SS-14	0.20	0.75	0.282	–	–	–	0.158	$\underline{\underline{K}}_{12}$
SS-15	0.20	0.75	0.280	–	–	–	0.187	$\underline{\underline{K}}_{13}$
SS-16	0.30	0.75	0.450	–	–	–	0.263	$\underline{\underline{K}}_{11}$
SSF-11	0.30	0.75	0.432	1.00	0	1.00	0.356	K_{11}
SSF-12	0.20	0.75	0.284	0.50	0	0.50	0.306	$\underline{\underline{K}}_{11}$
SSF-13	0.30	0.75	0.432	0.375	0	0.365	0.488	K_{11}
SSF-14	0.30	0.75	0.428	0.50	0	0.485	0.469	K_{11}
SSF-15	0.30	0.75	0.436	0.050	0.5	0.531	0.471	K_{11}
SSF-16	0.30	0.5	0.354	0.375	0	0.365	0.258	$\underline{\underline{K}}_{11}$
SSF-17	0.30	0.5	0.360	0.375	0.5	0.400	0.265	$\underline{\underline{K}}_{11}$

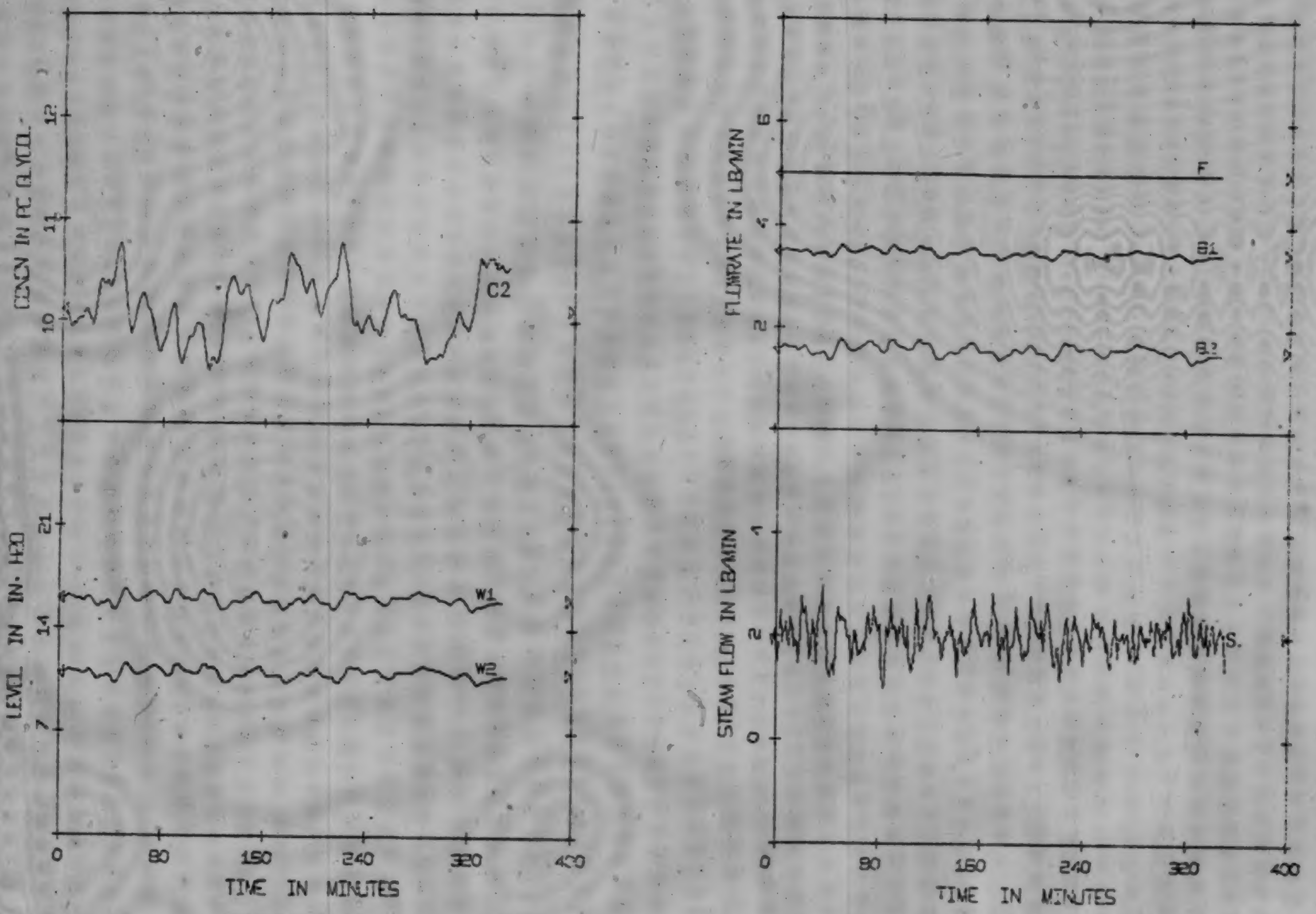


FIGURE 3.14 CLOSED LOOP SIMULATION DATA FOR RUN SS-12

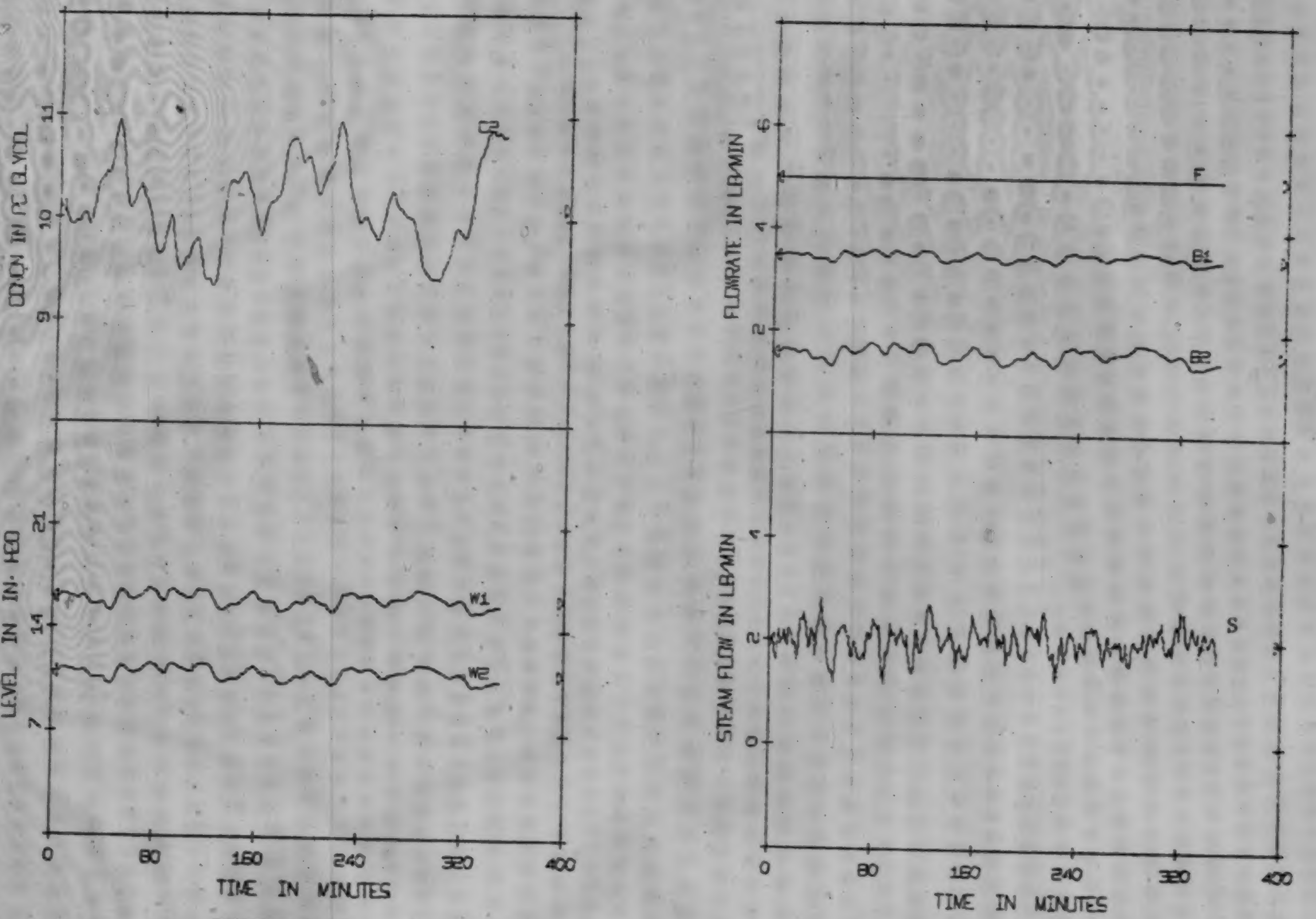


FIGURE 3.15 CLOSED LOOP

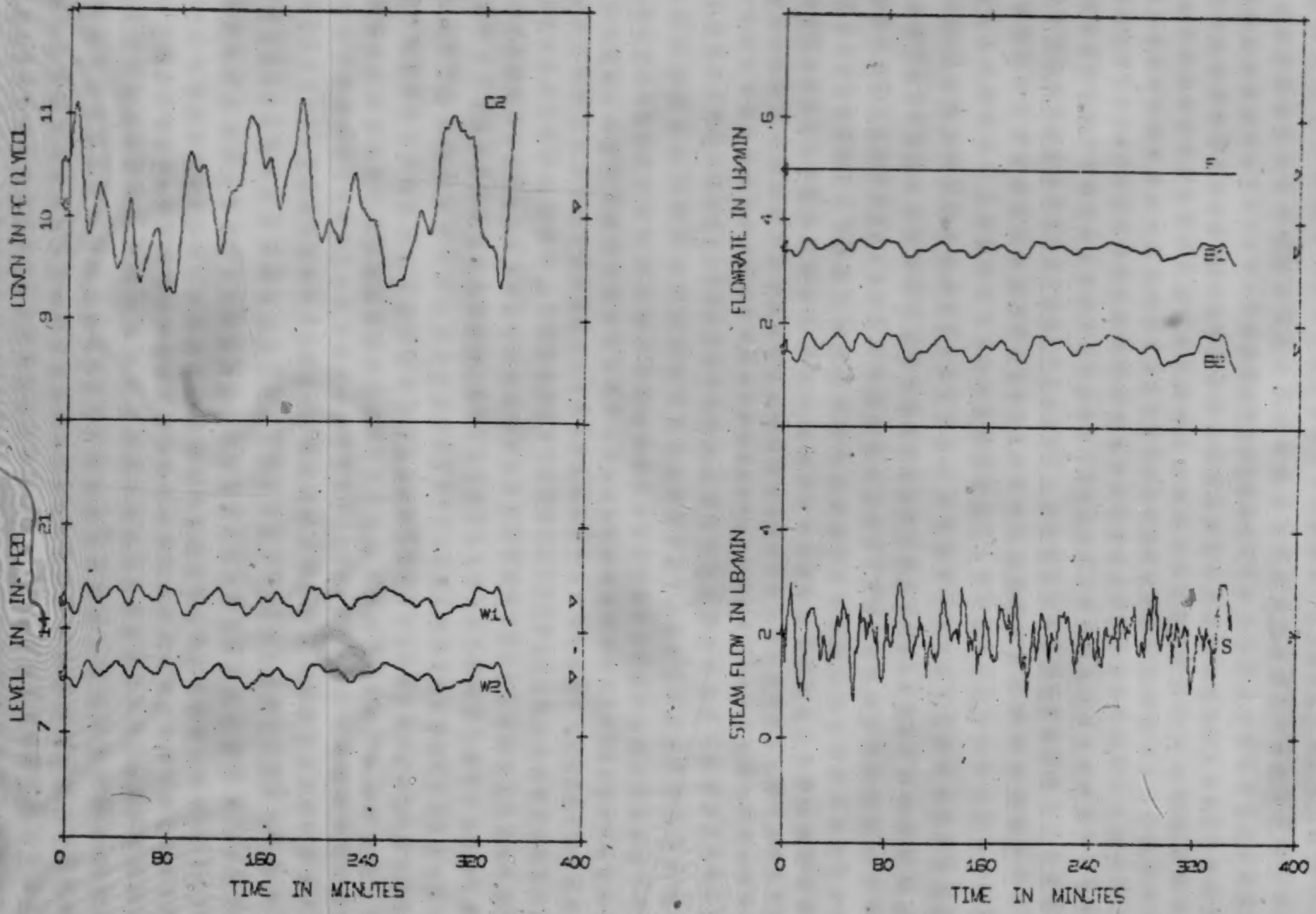


FIGURE 3.16 CLOSED LOOP SIMULATION DATA FOR RUN SS-16

$$K_{1i} = \begin{bmatrix} 0 & 0 & 0 & 0 & C_i \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 3 & 0 \end{bmatrix} \quad i = 1, 2, 3 \qquad (3.10)$$

with

$$C_1 = -2.5; \quad C_2 = -2.0; \quad C_3 = -1.5$$

3.7.1 Model Estimation : Steam Disturbances

Table 3.14 presents the models and parameter estimates for runs SS-11 to SS-16. For the runs SS-11 to SS-14, using controller matrix K_{12}, with steam flow disturbances only, the closed loop transfer function models obtained are in very good agreement. The variations in parameter values for most of the parameters are less than 1 percent. However, attempts to carry out simultaneous transfer function and noise model estimation were unsuccessful for all these runs. Simultaneous estimation resulted in large chi-square statistics even after a large number of iterations (>40). Hence first the transfer function model and then the noise model for the residual series were calculated. The sum of squares of residuals after fitting the transfer function model alone was very small.

For runs SS-11 and SS-12 the noise models are almost identical. It was not possible to fit reasonably any noise model with up to 5 parameters to the residuals from run SS-13. Furthermore, the chi-square test on the cross correlations for this run indicates little confidence in the transfer function model even though the fit seemed reasonably good from the small residual sum of squares.

TABLE 3.14

PARAMETER ESTIMATES FROM CLOSED LOOP SIMULATED DATA

(Steam disturbances, product concentration and level control)

Run No.	Closed Loop (**) Model	$\hat{\delta}_1$	$\hat{\delta}_2$	$\hat{\omega}_o$	$\hat{\omega}_1$	$\hat{\omega}_2$	$\hat{\phi}_1$	$\hat{\phi}_2$	$\hat{\theta}_1$	$^S/_Q$	$\Sigma a_t^2 \times 10^4$
SS-11	(2,2,1)	1.645	-0.684	0.0128	-0.0116	0.0081	-	-	-	24.9	
	(2,0,0)						0.849	0.103	-	54.48*	0.15
SS-12	(2,2,1)	1.645	-0.683	0.0128	-0.0115	0.0080				23.71	0.47
	(2,0,0)						0.657	0.102	-	57.88*	
SS-13	(2,2,1)	1.641	-0.680	0.0127	-0.0114	0.0076	-	-	-	62.40*	2.08
	(0,0,0)										
SS-14	(2,2,1)	1.644	-0.683	0.0128	-0.0116	0.0079	-	-	-	15.69	0.36
	(2,0,1)						1.856	-0.869	0.657	58.72*	0.36
SS-15[1]	(2,2,1)	1.630	-0.664	0.0124	-0.0113	0.0055	-	-	-	35.78*	28.4
	(0,0,0)										
SS-16[2]	(2,2,1)	1.445	-0.499	0.0136	-0.0103	0.000034	0.932	-	-0.409	32.55*	0.23
	(1,1,1)									32.88*	

[1] Control Matrix $\underline{K}_{13}$

[2] Control Matrix $\underline{K}_{11}$

** The closed loop model has the dither signal as the input

TABLE 3.15

OPEN LOOP PROCESS MODELS CALCULATED FROM CLOSED LOOP SIMULATED

(Steam disturbances, product concentration and level control)

Run No.	Open-Loop Model	$\hat{\delta}_1$	$\hat{\delta}_2$	$\hat{\omega}_o$	$\hat{\omega}_1$	$\hat{\omega}_2$	$\hat{\phi}_1$	$\hat{\phi}_2$	$\hat{\theta}_1$	Control Matrix
SS-11	(2,2,1) (2,0,0)	1.671	-0.661	0.0128	-0.0116	0.0081	0.849	0.103	-	$\underline{K}_{12}$
SS-12	(2,2,1) (2,0,0)	1.671	-0.660	0.0128	-0.0115	0.0080	0.657	0.102	-	$\underline{K}_{12}$
SS-13	(2,2,1) (0,0,0)	1.666	-0.657	0.0127	-0.0114	0.0076	-	-	-	$\underline{K}_{12}$
SS-14	(2,2,1) (2,0,1)	1.670	-0.660	0.0128	-0.0116	0.0079	1.856	-0.869	0.657	$\underline{K}_{12}$
SS-15	(2,2,1) (0,0,0)	1.649	-0.647	0.0124	-0.0113	0.0055	-	-	-	$\underline{K}_{13}$
SS-16	(2,2,1) (1,1,1)	1.479	-0.473	0.0136	-0.0103	0.000034	0.932	-	-0.409	$\underline{K}_{11}$

This was also the case for run SS-15. On the other hand, for run SS-16 with control matrix K_{11}, reasonable process and noise models were obtained by simultaneous estimation.

3.7.2 Comparison with Open Loop Models

Open loop process models calculated from these closed loop models using eqn. (2.23) are presented in Table 3.15. Comparing these results with open loop process models calculated from open loop simulation data in Table 3.2, indicate that significantly different process model orders are obtained from identification under closed loop and open loop identifications. Autoregressive parameter $\hat{\delta}_1$ is nearly equal to the estimate obtained using open loop runs SS-4 and SS-6. The estimate of $\hat{\delta}_2$ from the closed loop runs is almost equal to the value obtained from run SS-6. Similarly, the estimates for $\{\omega_j\}$ are comparable to those obtained from open loop runs.

Although the closed loop runs have produced consistent parameter estimates (runs SS-11 to SS-15), the chi square test indicates very little confidence in the model orders. Hence the open loop models seem to be more reliable in this identification study.

3.7.3 Model Estimation: Steam and Feed Flow Disturbances

The parameter estimates for simulation runs with steam and feed flow disturbances are presented in Table 3.16. With the exception of run SSF-11, the estimated process model parameters remain fairly constant with variations of less that 1 percent. The noise models in the five cases are second order with one degree of

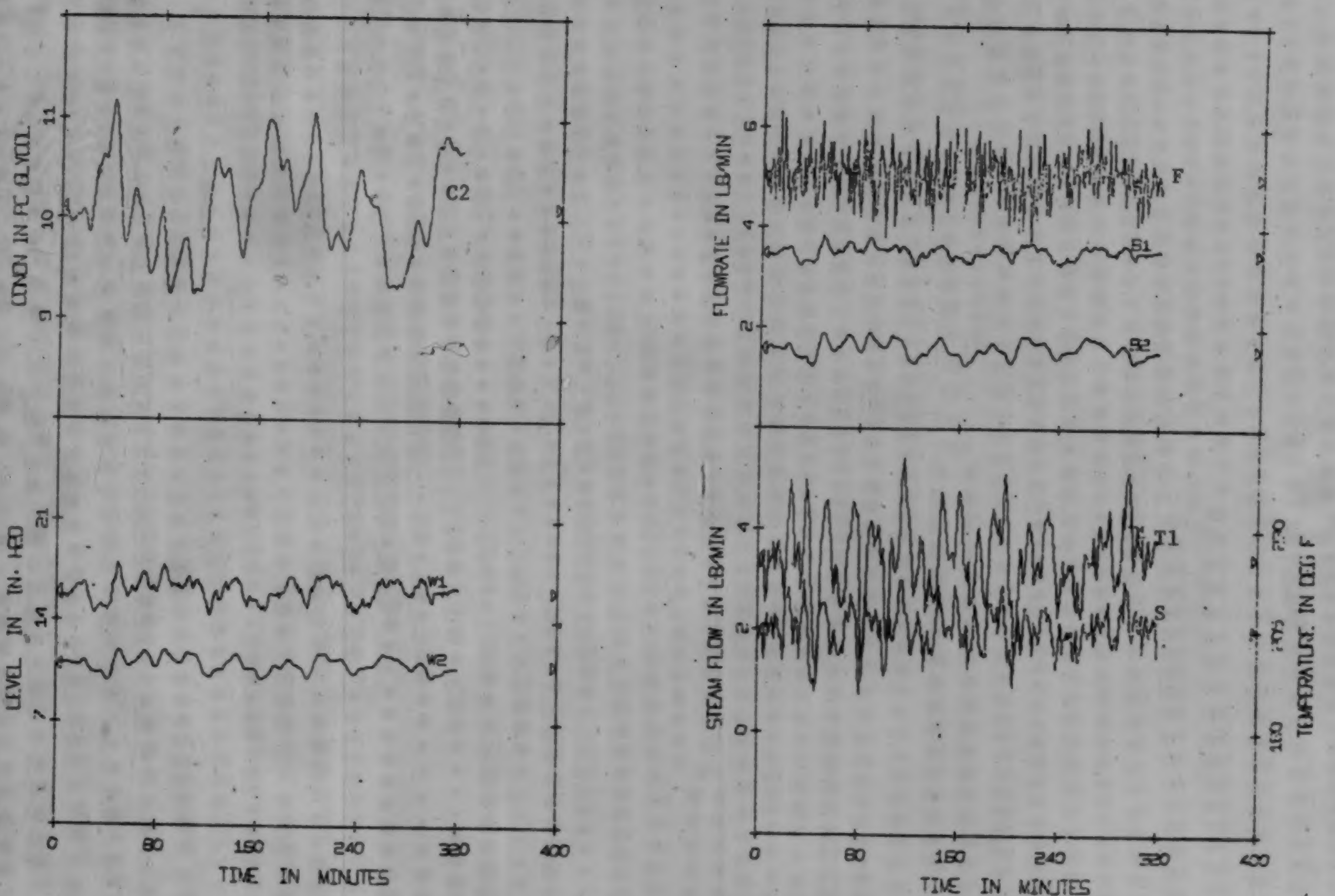


FIGURE 3.17 CLOSED LOOP SIMULATION DATA FOR RUN SSF-14

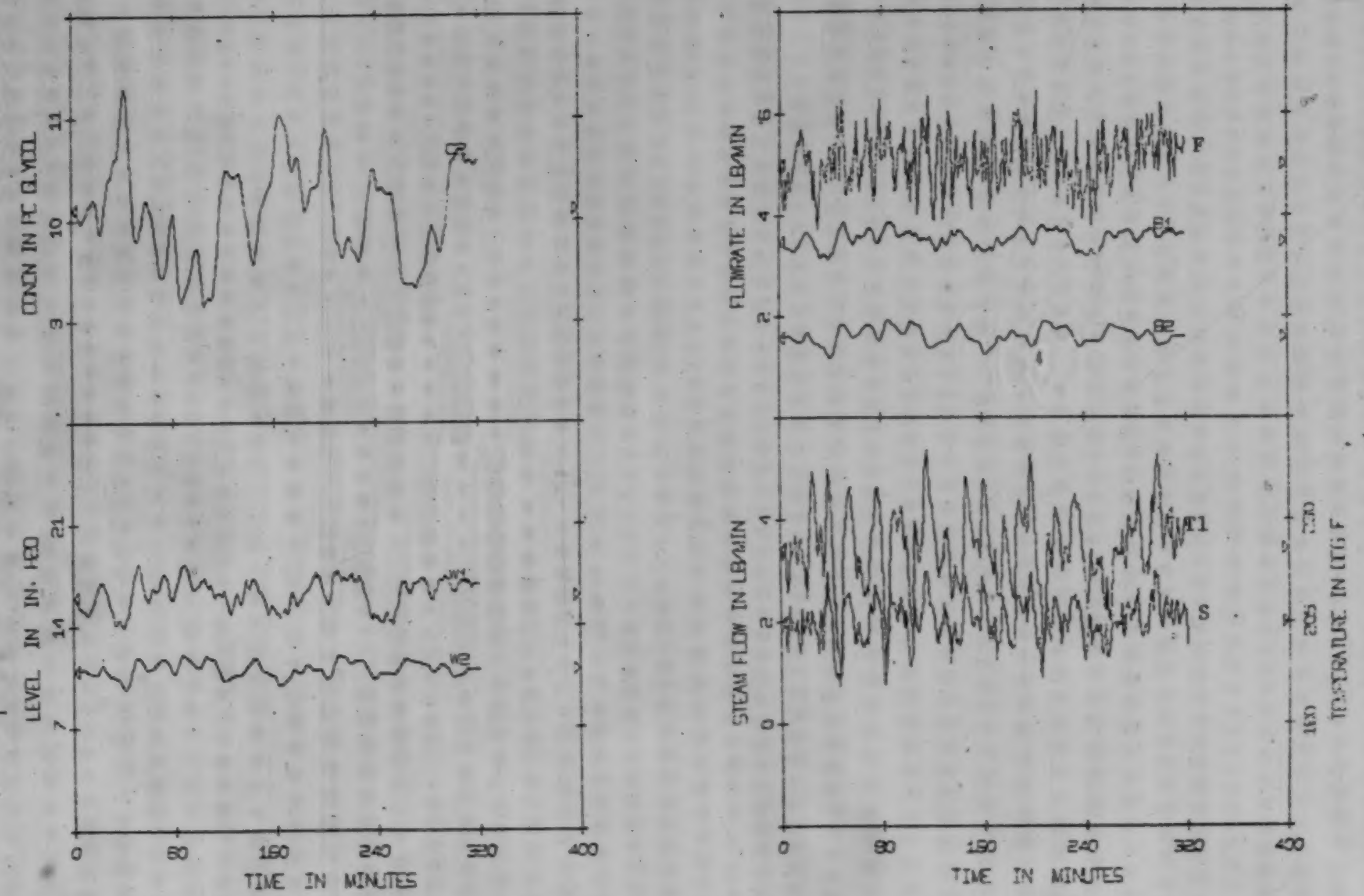


FIGURE 3.18 CLOSED LOOP SIMULATION DATA FOR RUN SSF-15

TABLE 9.16

PARAMETER ESTIMATES FROM CLOSED LOOP SIMULATION DATA

(Steam and feed flow disturbances, product concentration and level control)

Run No	Closed loop Model **	$\hat{\delta}_1$	$\hat{\delta}_2$	$\hat{\omega}_0$	$\hat{\omega}_1$	$\hat{\phi}_1$	$\hat{\phi}_2$	$\hat{\theta}_1$	S_{aa}	Q_a	Σa_t^2 $\times 10^4$
SSF-11	(2,1,1) (2,1,1)	1.375	-0.437	0.0131	-0.0112	1.241	-0.401	-0.258	16.00	21.65	2.87
SSF-12	(2,1,1) (2,1,0)	1.446	-0.501	0.0137	-0.0105	1.047	-0.223	--	23.56	24.02	1.35
SSF-13	(2,1,1) (2,1,1)	1.415	-0.472	0.0135	-0.0107	1.311	-0.448	-0.191	16.16	22.83	0.763
SSF-14	(2,1,1) (1,1,1)	1.432	-0.487	0.0136	-0.0107	0.797	—	-0.261	19.78	24.60	1.35
SSF-15	(2,1,1) (2,1,1)	1.402	-0.460	0.0133	-0.0108	1.219	-0.372	-0.281	17.36	28.76	1.42
SSF-16	(2,1,1) (1,1,1)	1.423	-0.476	0.0138	-0.0107	0.766	—	-0.232	14.94	19.69	0.739
SSF-17	(2,1,1) (2,1,1)	1.423	-0.478	0.0135	-0.0105	1.265	-0.407	-0.213	14.03	20.94	0.748

** The closed loop model has the dither signal as the input

TABLE 3.17

OPEN LOOP PROCESS MODELS OBTAINED USING CLOSED LOOP SIMULATIONS

(Steam and feed flow disturbances, product concentration and level control)

Run No	Open loop Model	$\hat{\delta}_1$	$\hat{\delta}_2$	$\hat{\omega}_0$	$\hat{\omega}_1$	$\hat{\phi}_1$	$\hat{\phi}_2$	$\hat{\theta}_1$
SSF-11	(2,1,1) (2,1,1)	1.409	-0.409	0.0138	-0.0112	1.241	-0.401	-0.258
SSF-12	(2,1,1) (2,1,0)	1.480	-0.474	0.0137	-0.0105	1.047	-0.223	--
SSF-13	(2,1,1) (2,1,1)	1.449	-0.448	0.0135	-0.0107	1.311	-0.448	-0.191
SSF-14	(2,1,1) (1,1,1)	1.466	-0.460	0.0136	-0.0107	0.797	--	-0.261
SSF-15	(2,1,1) (2,1,1)	1.435	-0.433	0.0132	-0.0108	1.219	-0.372	-0.287
SSF-16	(2,1,1) (1,1,1)	1.457	-0.449	0.0138	-0.0107	0.766	--	-0.232
SSF-17	(2,1,1) (2,1,1)	1.457	-0.452	0.0135	-0.0105	1.264	-0.407	-0.213

differencing. The noise model for runs SS-11, 13, 15 and 17 is (2, 1,1) and the parameters are within 10 percent of each other. Similarly for runs SSF-14 and 16 with noise model (1, 1, 1), parameters ϕ_1, θ_1 are nearly equal.

For all the runs, the chi square statistics are fairly low indicating good fits were obtained.

Table 3.17 presents the open loop process models calculated from the identified closed loop models for runs SSF-11 to SSF-17. As could be expected from the closed loop models, the parameter estimates here are almost equal, when compared with the parameter estimates for open loop runs SSF-1 to SSF-4. In Table 3.6 the parameter estimates from the closed loop runs are within 5 - 10 percent of the open loop values.

Here, both identification techniques produce reliable models with adequately small values of $S_{\alpha a}$ and Q_a indicating good overall fits.

3.8 Closed Loop Identification Experiments

Five runs, SF-11 to SF-15, were made using dither signals, feed flow disturbance sequences and feedback controller matrices. The run conditions are given in Table 3.18 and typical plots are shown in Figs. 3.19 to 3.21.

The various control matrices that were used are:

$$\underline{\underline{K}}_{11} = \begin{bmatrix} 0 & 0 & 0 & 0 & -2.5 \\ 1.0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 3.0 & 0 \end{bmatrix}$$

TABLE 3.18

CLOSED LOOP IDENTIFICATION EXPERIMENTS

(Steam and feed flow disturbances, product concentration
and levels under control)

Run No	Steam (1b/min)			Feed (1b/min)			Concentration (% glycol)		Controller
	σ_{input}	ϕ_S	σ_S	σ_{input}	ϕ_F	σ_F	σ_{C2}	C2(0)	matrix, $\underline{K}$
SF-11	0.125	0.75	0.203	0.10	0.50	0.117	0.251	9.6	$\underline{K}_{11}$
SF-12	0.125	0.50	0.159	0.15	0	0.149	0.134	9.7	$\underline{K}_{11}$
SF-13	0.125	0.50	0.157	0.10	0	0.103	0.140	9.0	$\underline{K}_{11}$
SF-14	0.125	0.75	0.226	0.20	0.50	0.226	0.196	9.6	$\underline{K}_{14}$
SF-15	0.125	0.75	0.265	0.20	0.50	0.228	0.127	9.8	$\underline{K}_{15}+\underline{K}_I$

TABLE 3.18

CLOSED LOOP IDENTIFICATION EXPERIMENTS

(Steam and feed flow disturbances, product concentration and levels under control)

Run No	Steam (lb/min)			Feed (lb/min)			Concentration (% glycol)		Controller matrix, $\underline{\underline{K}}$
	σ_{input}	ϕ_S	σ_S	σ_{input}	ϕ_F	σ_F	σ_{C2}	C2(0)	
SF-11	0.125	0.75	0.203	0.10	0.50	0.117	0.251	9.6	$\underline{\underline{K}}_{11}$
SF-12	0.125	0.50	0.159	0.15	0	0.149	0.134	9.7	$\underline{\underline{K}}_{11}$
SF-13	0.125	0.50	0.157	0.10	0	0.103	0.140	9.0	$\underline{\underline{K}}_{11}$
SF-14	0.125	0.75	0.226	0.20	0.50	0.226	0.196	9.6	$\underline{\underline{K}}_{14}$
SF-15	0.125	0.75	0.265	0.20	0.50	0.228	0.127	9.8	$\underline{\underline{K}}_{15}+\underline{\underline{K}}_{I}$

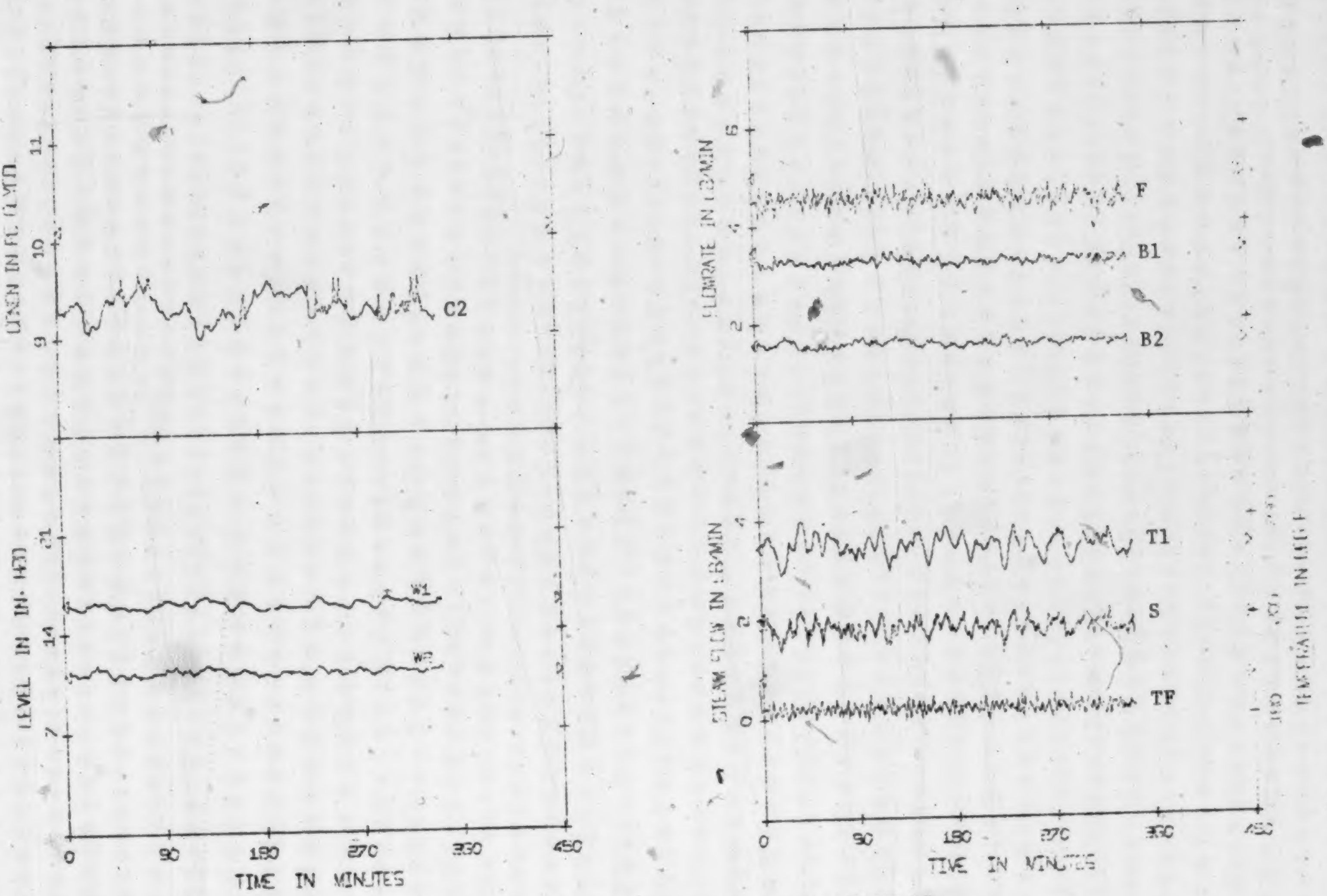


FIGURE 3.19 CLOSED LOOP EXPERIMENTAL DATA FOR RUN SF-12

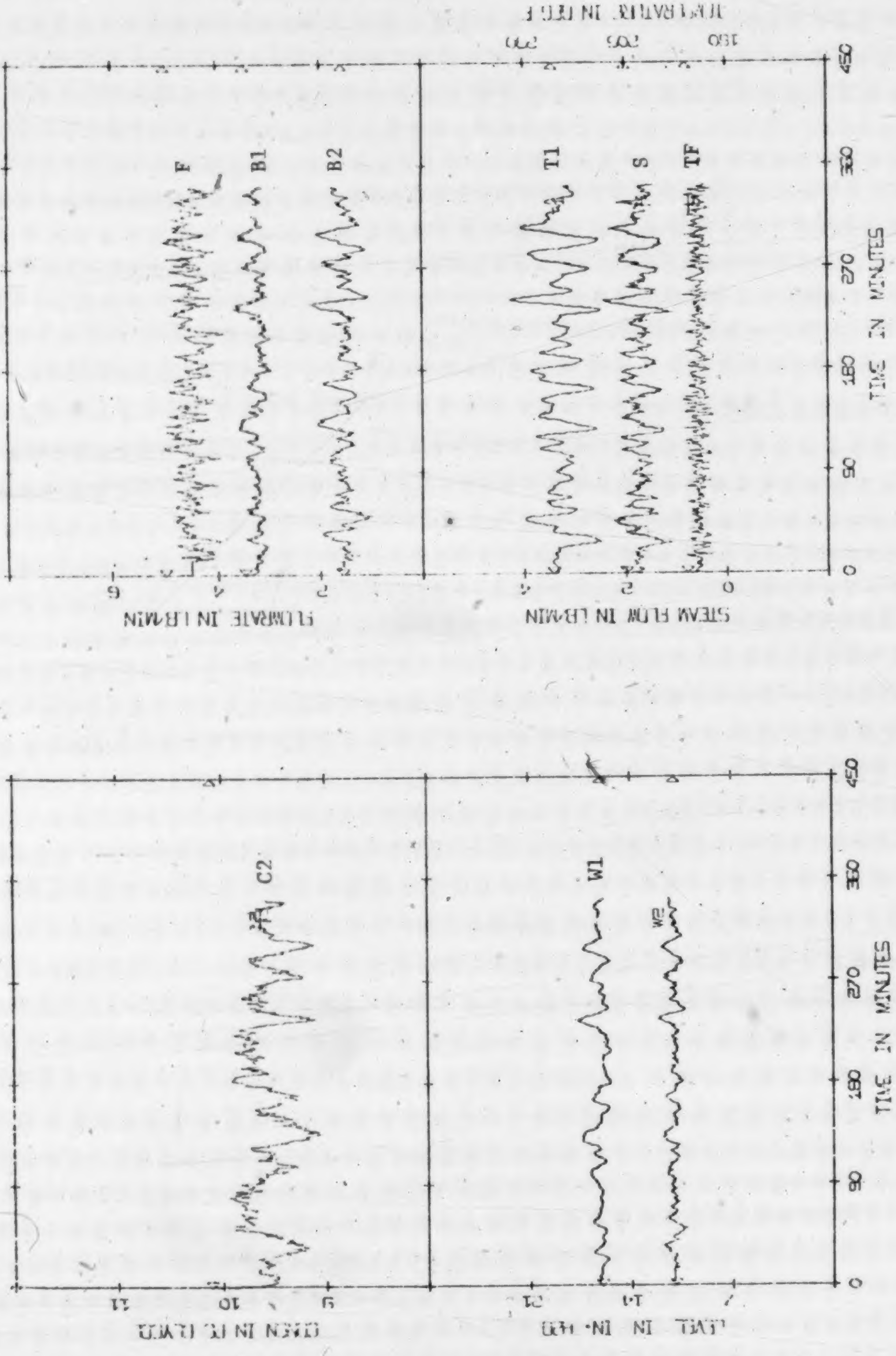


FIGURE 3.20 CLOSED LOOP EXPERIMENTAL DATA FOR RUN SF-14

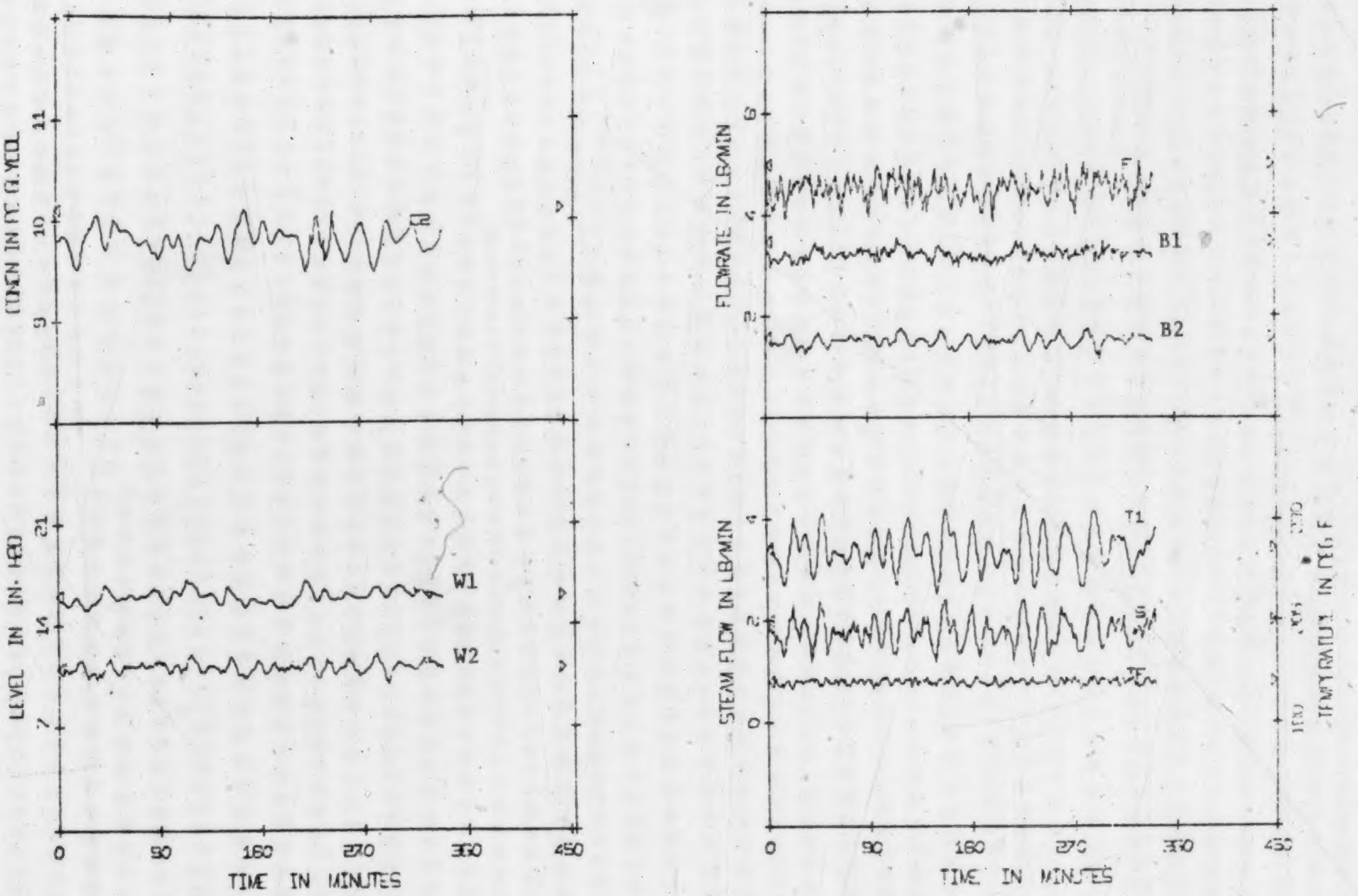


FIGURE 3.21 CLOSED LOOP EXPERIMENTAL DATA FOR RUN SF-15

$$\underline{K}_{14} = \begin{bmatrix} 0 & 0 & 0 & 0 & -4.89 \\ 1.5 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 6.5 & 0 \end{bmatrix}$$

$$\underline{K}_{15} = \begin{bmatrix} 0 & 0 & 0 & 0 & -9.554 \\ 1.0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 3.0 & 0 \end{bmatrix}$$

For run SF-15 an integral control matrix $\underline{K}_I$ was used in addition to proportional control matrix, $\underline{K}_{15}$.

$$K_I = \begin{bmatrix} 0 & 0 & 0 & 0 & -0.3582 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

The proportional-integral control law used is

$$\underline{u}(t) = \underline{K}_{15}\,\underline{x}(t) + \underline{K}_I\Big(\sum_{n=1}^{t} x(n)\Big)\frac{\Delta T}{60} \qquad (3.11)$$

As was observed in the closed loop simulations, the standard deviation of the product concentration was reduced when feedback control was used.

3.8.1 Closed Loop Process Models

Parameter estimates for the runs SF-11 to SF-15 are presented in Table 3.19. The process model with orders (r, s, b) $\equiv$ (2, 1, 1) provided good fits for runs SF-11 to SF-15 in spite of the different controllers used. For runs SF-11 to SF-13 with

TABLE 3.19

PARAMETER ESTIMATES FOR CLOSED LOOP EXPERIMENTS

(Steam and feed flow disturbances, Product concentration and level control)

Run No	Closed loop ** Model	$\hat{\delta}_1$	$\hat{\delta}_2$	$\hat{\omega}_0$ $\times 10^2$	$\hat{\omega}_1$ $\times 10^2$	$\hat{\phi}_1$	$\hat{\phi}_2$	$\hat{\theta}_1$	$S_{\alpha a}$	Q_a	Σa_t $\times 10^3$
SF-11	(2,1,1) (2,1,0)	1.719	-0.812	0.394	0.563	-0.233	0.869	--	26.48	37.71*	0.139
SF-12	(2,1,1) (1,0,0)	1.648	-0.869	0.363	0.327	0.826	--	--	23.45	45.49*	0.175
SF-13	(2,1,1) (2,1,0)	1.697	-0.755	0.108	-0.038	-0.482	-0.211	--	16.23	13.48	0.150
SF-14	(2,1,1) (2,1,1)	1.501	-0.564	-0.314	-0.187	-1.045	-0.343	-0.600	19.82	34.32*	0.240
SF-15	(2,1,1) (2,0,1)	1.687	-0.849	-0.086	0.124	1.738	-0.820	0.453	22.16	44.97*	0.037

* Values of $S_{\alpha a}$ or Q_a larger than $\chi^2_{0.05}$

** Closed loop model has the dither signal as the input.

TABLE 3.20

OPEN LOOP PROCESS MODELS OBTAINED USING CLOSED LOOP EXPERIMENTS

(Steam and feed flow disturbances, product concentration and level control)

Run No.	Open-Loop Model	$\hat{\delta}_1$	$\hat{\delta}_2$	$\hat{\omega}_o \times 10^2$	$\hat{\omega}_1 \times 10^2$	$\hat{\phi}_1$	$\hat{\phi}_2$	$\hat{\theta}_1$
SF-11	(2,1,1) (2,1,0)	1.729	-0.826	0.394	0.563	0.233	0.869	-
SF-12	(2,1,1) (1,0,0)	1.655	-0.848	0.367	0.331	0.826	-	-
SF-13	(2,1,1) (2,1,0)	1.703	-0.757	0.109	0.038	0.482	0.211	-
SF-14**	(2,1,1) (2,1,1)	1.572	-0.555	-0.317	-1.841	1.045	0.343	-0.600
SF-15	(2,1,1) (2,0,1)	1.705	-0.844	0.864	-0.124	1.738	-0.820	0.453

** Level control as in Eqn. (3.9) or Run SF-5 control matrix K_{11}, the $\hat{\delta}_1$ values were almost equal, being within 1 percent of each other. The δ_2 values showed slightly larger variations of approximately 5 percent. Parameters $\hat{\omega}_0$ and $\hat{\omega}_1$ obtained from runs SF-11 and SF-12 have comparable magnitudes but for runs SF-13 they differ by factors of 3-10.

Table 3.19 indicates that although the fits are good for all runs, both with respect to the residual sum of squares and chi square tests, the model parameters are sensitive to change in process conditions and the control matrix.

The closed loop study shows that models with transfer function model orders (2, 1, 1) have provided good fits for all runs but simulation runs SS-11 to SS-16. As discussed in §3.6.1, the $\{\hat{\delta}_j\}$ are 10-15 percent higher in the case of models derived from experimental data, when the identical controller matrices are used. The $\{\hat{\omega}_j\}$ are higher for models estimated from simulation data. For closed loop study the simulation data with a steam dither signal only, produced models with different model orders and in many cases simultaneous fitting of transfer function and noise models was not possible. With this exception, other fits are generally good in both simulation and experimental studies.

3.8.2 Comparison with Open Loop Models

By using eqn. (2.23) open loop process models were calculated from the identified closed loop process models. These are presented in Table 3.20. The level control systems for runs SF-1 to 4 (cf. Table 3.11) and SF-11, 12, 13, 15 are the same. Comparison of these runs indicate that δ_1 from closed loop data is fairly close to the values from open loop data. Parameter δ_2 in runs SF-11 and SF-13 compare well with that for runs SF-1, 3, 4. ω_o and ω_1 values are of comparable magnitudes, but exhibit some variations, as was the case for the open loop runs. ω_o is smaller than that obtained using open loop data, by about a factor of two.

The small values of $S_{\alpha a}$ in Tables 3.11 and 3.19 for these open loop and closed loop runs, indicate that in general good transfer function models were obtained.

Since larger Q_a values were obtained for the closed loop runs than for the open loop runs, this suggests that the noise models identified under closed loop conditions are less reliable.

3.9 Conclusions

Evaporator models calculated from both open loop and closed loop data demonstrate that the time series modelling technique presented by Box and Jenkins [1] can be successfully used to model real processes. The extremely small sum of squares of residuals indicated a very good fit to both experimental and simulation data.

Process transfer function models obtained from simulation data containing "unknown" disturbances are fairly invariant whereas the noise models are sensitive to process conditions (e.g. type and magnitude of disturbances). For process models developed from experimental data, the estimated autoregressive parameters were constant (for given set of level control constants) but there were large variations in the moving average parameters. The fit of data is again very good, even in the presence of significant process disturbances.

The utility of the time series modelling technique was tested for processes under closed loop operating conditions. The resulting open loop process models calculated from the closed loop data were nearly the same as the open loop process models obtained from open loop data. Hence it can be concluded that time series analysis technique proves to be a useful modelling technique for processes operating under open or closed loop conditions.

An overall comparison of the models, calculated from experimental and simulation data, indicates that for both open loop and closed loop conditions, comparable models were obtained. Higher $\{\hat{\delta}_j\}$ values were obtained from the experimental study, whereas significantly higher $\{\omega_i\}$ estimates were calculated for the simulation data. No significant difference in noise model orders was observed. Similarly, with the exception of simulations using steam disturbances only, comparable and adequate fits were obtained using simultaneous transfer function and noise model fitting.

The choice of input signal plays an important role in identification processes. Where the variance of input is constrained, use of first order autoregressive input signal with positive parameter ϕ produced better excitation of the process and also reduces the width of confidence intervals on the parameter estimates.

CHAPTER FOUR

EVALUATION OF MINIMUM MEAN SQUARE ERROR CONTROLLERS

4.1 Introduction

In this chapter controllers are designed using the evaporator models that were reported in Chapter Three. The noise models are used to forecast future disturbances and the transfer function models are used to take appropriate compensatory action. The resulting controllers are referred to as minimum mean square error (MMSE) controllers.

In this chapter the performance of these MMSE controllers is evaluated and compared to the results obtained using conventional PI control or no control in the same disturbance environment. This comparison is carried out using simulated responses from the state space evaporator model and then using experimental data from the actual pilot plant evaporator. The robustness of the MMSE controllers is tested using deterministic disturbances such as step changes.

4.2 Evaluation of MMSE Controllers : Simulation Study

The MMSE controllers designed based on open loop identification runs SSF-1 to SSF-4 and closed loop runs SSF-11, 12 and 14, are presented in Table 4.1. The performance of these controllers was studied for stochastic disturbances and deterministic disturbances such as step changes in feed flow rate.

If the noise model has a pole on the unit circle, then the resulting controller provides integral action [5] and thus eliminates offsets due to step disturbances. For this reason noise models with

TABLE 4.1

MMSE CONTROLLERS DESIGNED USING MODELS FROM SIMULATION RUNS

No.	Run No.	Controller, C(B)
1	SSF-1	$\frac{123.96 - 251.04\ B + 160.28\ B^2 - 32.89\ B^3}{1 - 1.1654\ B - 0.4482\ B^2 + 0.6136\ B^3}$
2	SSF-2	$\frac{108.68 - 233.86\ B + 161.29\ B^2 - 35.91\ B^3}{1 - 1.2630\ B - 0.3785\ B^2 + 0.6414\ B^3}$
3	SSF-3	$\frac{206.47 - 480.13\ B + 413.72\ B^2 - 163.11\ B^3 + 25.23\ B^4}{1 - 1.8757\ B + 0.2865\ B^2 + 1.1196\ B^3 - 0.5304\ B^4}$
4	SSF-4	$\frac{218.68 - 492.33\ B + 423.21\ B^2 - 167.97\ B^3 + 26.53\ B^4}{1 - 1.8449\ B + 0.1947\ B^2 + 1.2170\ B^3 - 0.5631\ B^4}$
5	SSF-11	$\frac{144.23\ B - 322.67\ B + 256.53\ B^2 - 90.02\ B^3 + 11.95\ B^4}{1 - 1.4301\ B - 0.1748\ B^2 + 0.9304\ B^3 - 0.3255\ B^4}$
6	SSF-12	$\frac{149.96 - 315.00\ B + 225.22\ B^2 - 68.35\ B^3 + 7.76\ B^4}{1 - 1.2792\ B - 0.3014\ B^2 + 0.7520\ B^3 - 0.1714\ B^4}$
7	SSF-14	$\frac{113.27 - 224.80\ B + 138.23\ B^2 - 27.03\ B^3}{1 - 1.0045\ B - 0.6264\ B^2 + 0.6319\ B^3}$

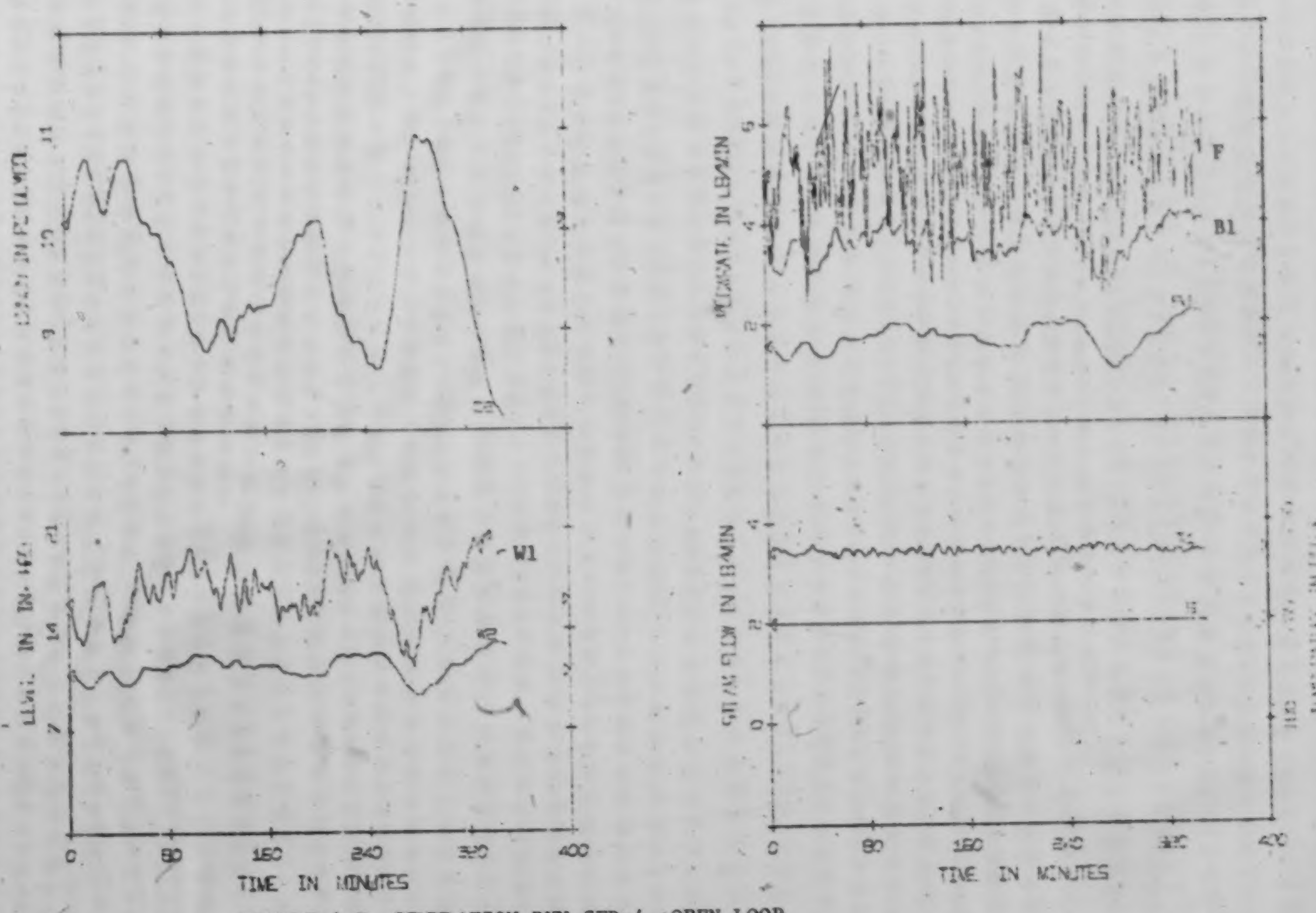


FIGURE 4.1 SIMULATION RUN SFD-4 :OPEN LOOP

one degree of differencing were selected for controller design whenever such a noise model indicated good fit. Of the seven closed loop runs SSF-11 to SSF-17, three runs (SSF-11, 12 and 14) with different noise model orders were arbitrarily chosen for controller design.

Simulation runs were made for four different first order autoregressive disturbances, SFD-1 to 4, and three different step changes in feed flow rate, SFS-1 to 3. The step changes consisted of a step increase at $t = 5$ and a step decrease of equal magnitude at $t = 205$. In all the runs the levels were controlled using proportional control matrix $\underset{\sim}{K}_1$. The product concentration was under MMSE control with steam flow as the manipulated variable. The steam flow adjustments were constrained as $-1.0 \leq u_1 \leq 0.5$ where $u_1 = (S - \bar{S})/S$ and $\bar{S}$ is the normal steady state value. Two PI controller settings were used for the runs with PI controllers. The first set of controller constants, KP = -9.55 and KI = -0.358, were obtained by King and McNeill [23] by experimentally tuning the product concentration control loop. A second set, KP = -40.6 and KI = -0.36 was obtained from simulation data by tuning the PI controller to minimize the integral squared error (ISE) performance criterion for stochastic disturbances ($\sigma_F = 0.75$, $\phi_F = 0.75$). Runs with no concentration control are also presented for purposes of comparison.

4.2.1 Performance Under Stochastic Disturbances

The run conditions and the corresponding standard deviations obtained using 320 data points are presented in Table 4.2. Figures

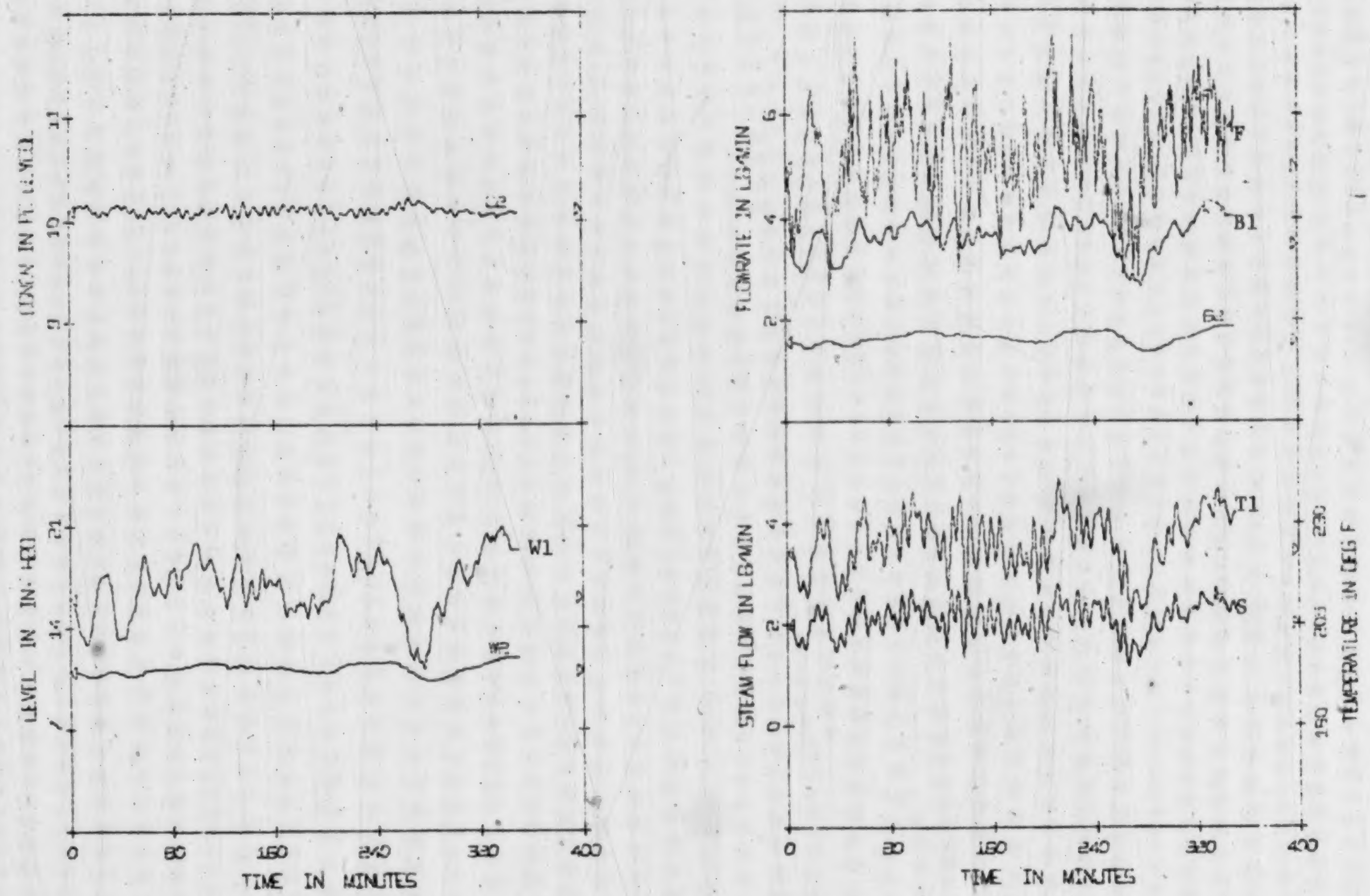


FIGURE 4.2 SIMULATION RUN SFD-3 : PI(sim) CONTROLLER

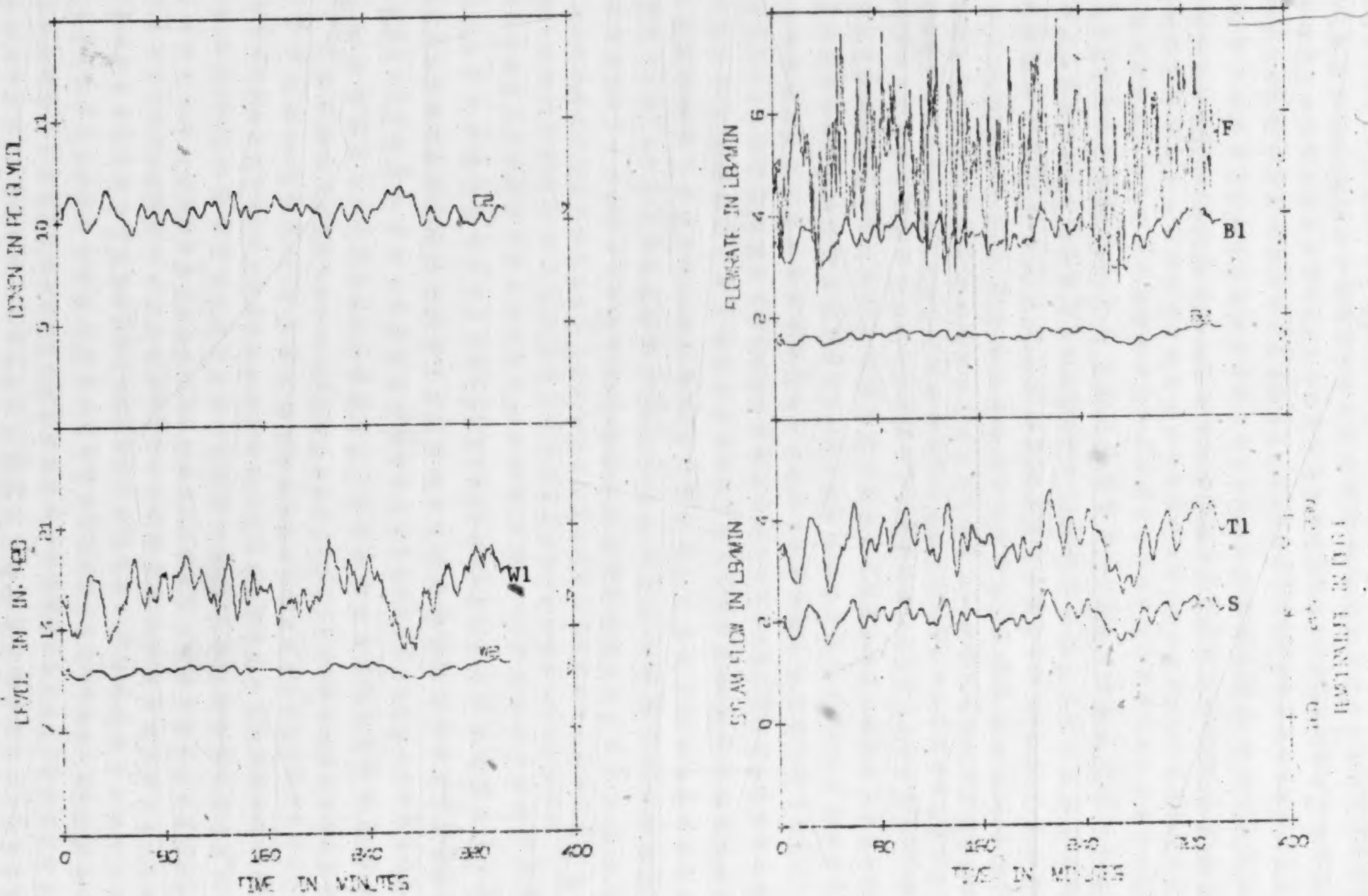


FIGURE 4.3 SIMULATION RUN SFD- 4: PI(exp) CONTROLLER

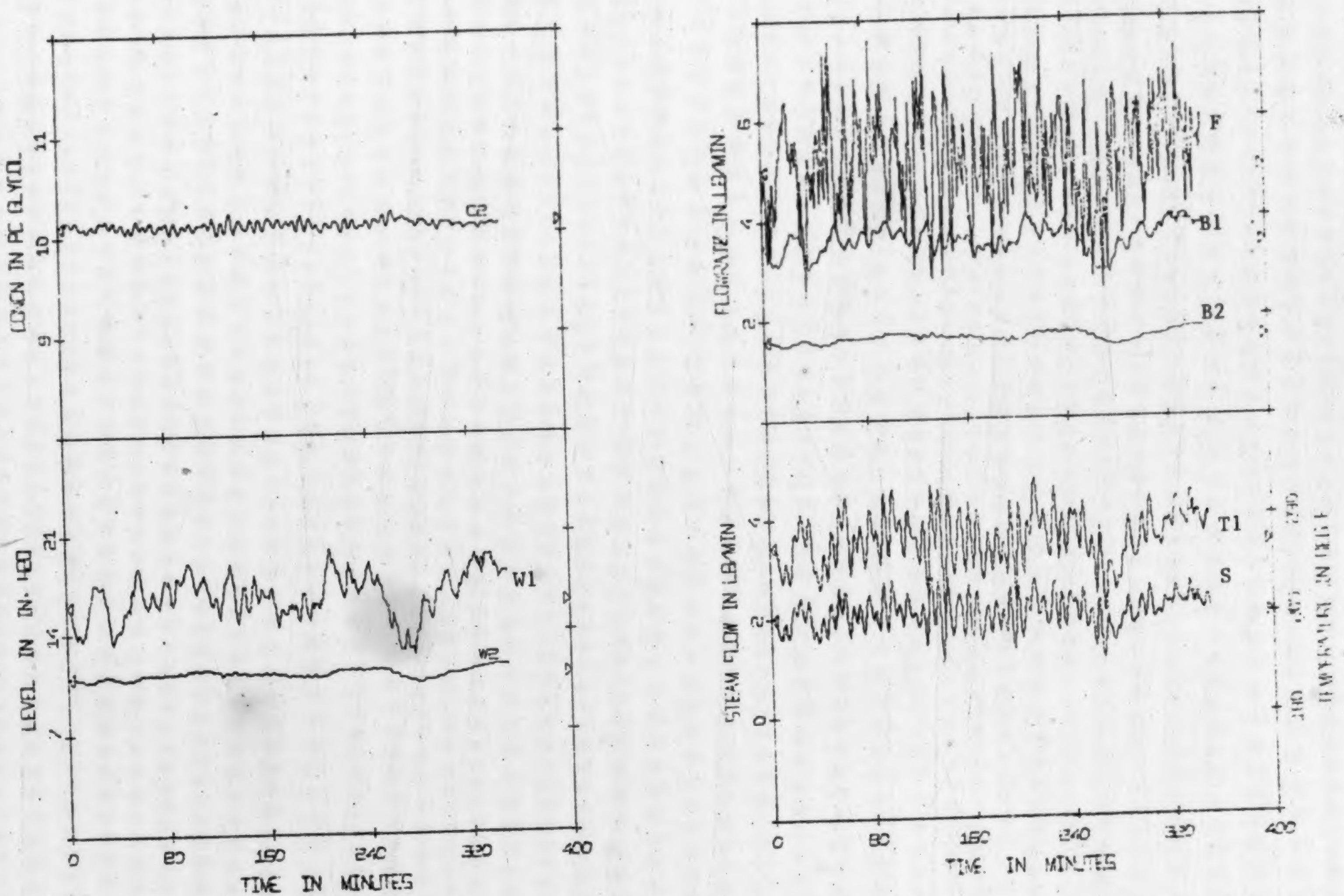


FIGURE 4.4 SIMULATION RUN SFD-4 : PI(sim) CONTROLLER

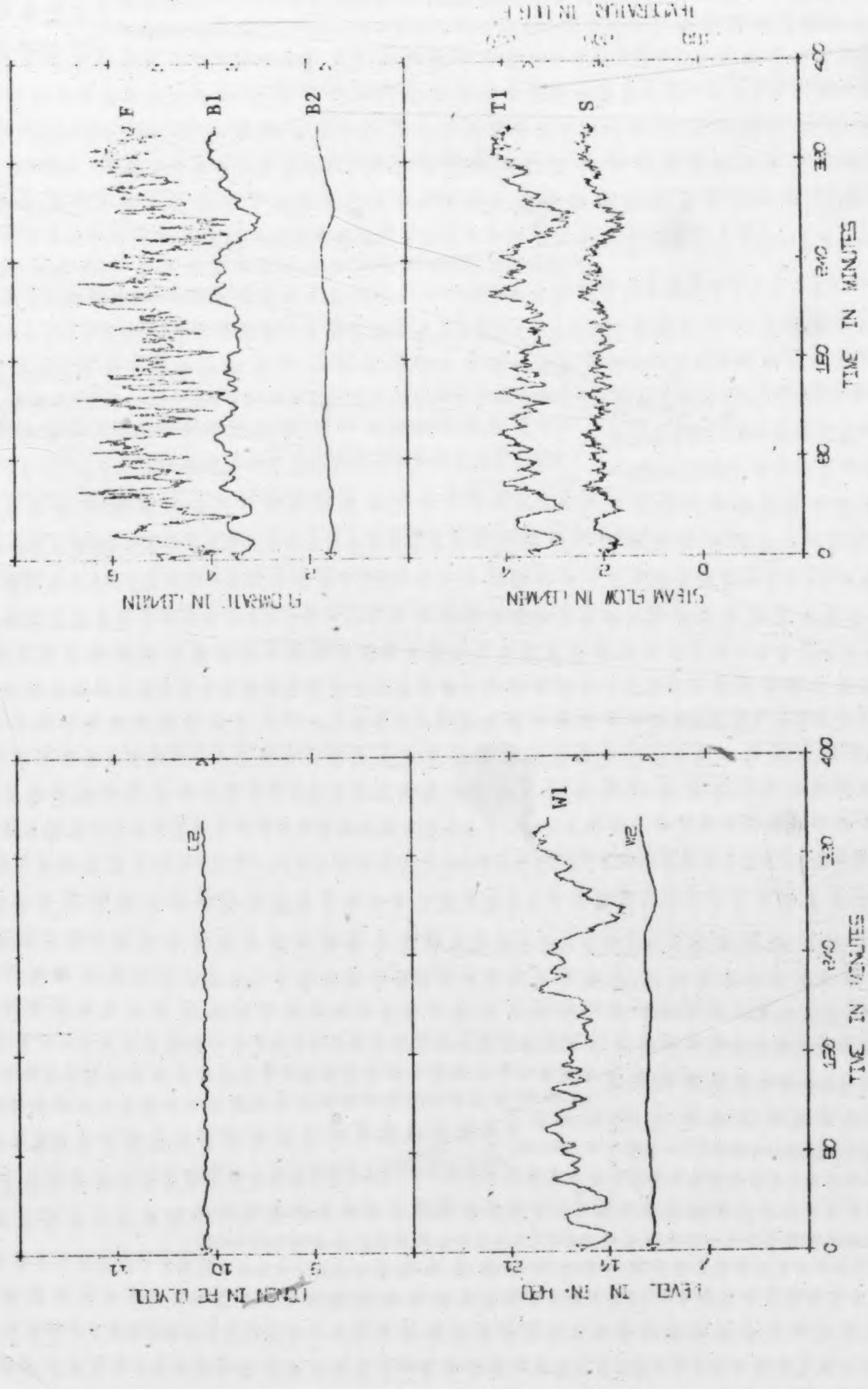


FIGURE 4.5 SIMULATION RUN SFD-2 : MMSE CONTROLLER #2

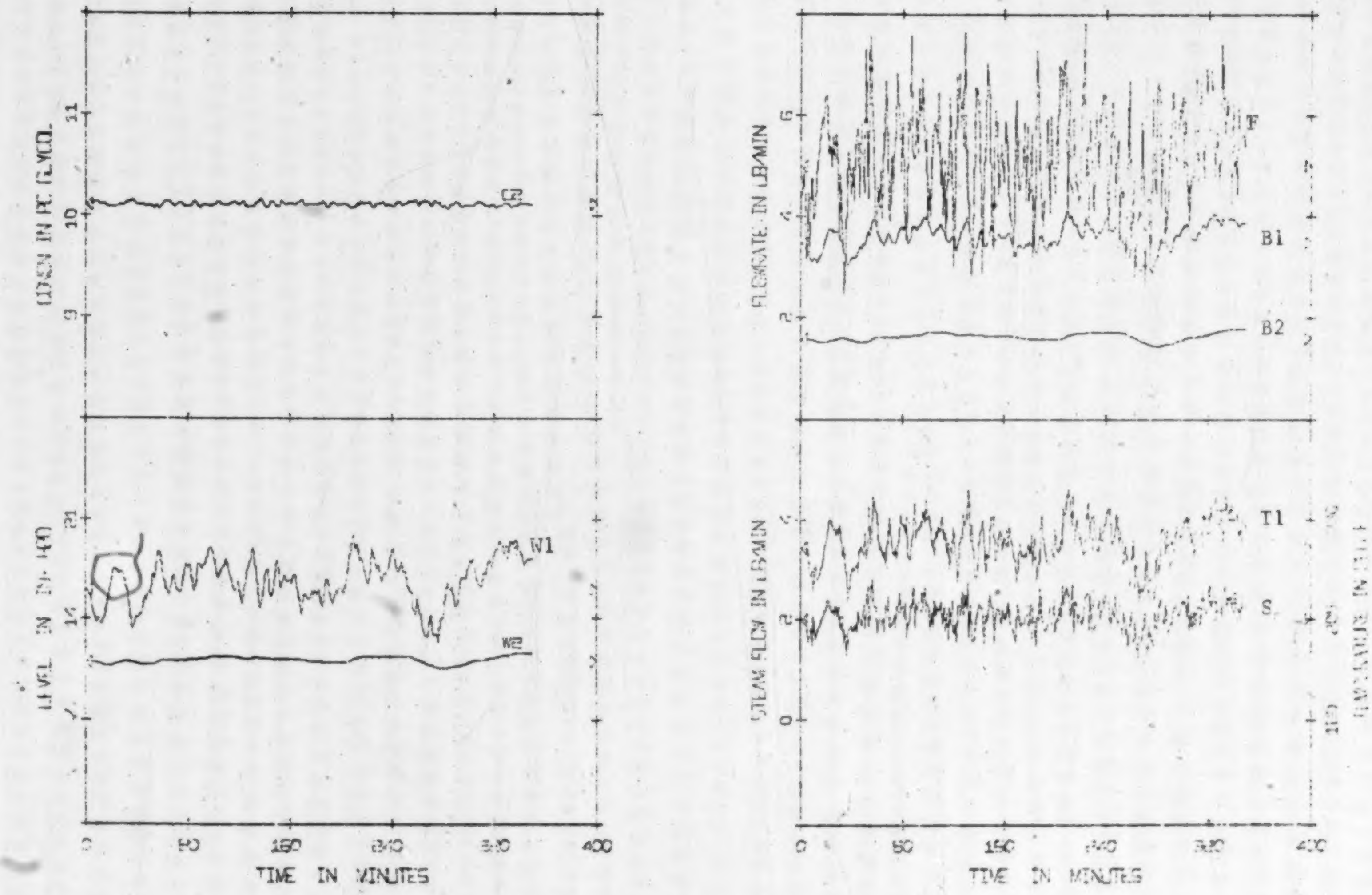


FIGURE 4.6. SIMULATION RUN SFD-4 : MMSE CONTROLLER #2

4.1 to 4.4 compare responses for open loop and PI controls and Fig. 4.5 and 4.6 show responses for the MMSE controller #2 for run conditions SFD-2 and SFD-4. Figures 4.7 and 4.8 present responses using MMSE controller #5, for the same set of random number sequences.

It can be seen from Table 4.2 that as expected, both PI and MMSE controllers provide significant improvement over the open loop responses. Controller #4 based on run SSF-4 was found to be unstable under all run conditions, when no constraints were present on the manipulated variable. For this controller the response consisted of oscillations with slowly increasing amplitudes of the manipulated and controlled variable, thus indicating instability. When contraints were imposed on the manipulated variable the response in Fig. 4.9 was obtained. It can be clearly seen that the controller performance is not satisfactory since the manipulated variable frequently hits the constraints and the C2 response contains undesirable oscillations. The other three controllers based on open loop identifications performed well and provided better control than the two PI controllers.

For the case of the MMSE controllers #5 to 7, based on closed loop identification runs, all the controllers performed as well as the other MMSE controllers when stochastic disturbances were considered. As can be seen from Table 4.2, MMSE controllers produced standard deviations of errors, σ_{C2}, which are approximately one third of those obtained using PI (sim). The MMSE controllers based on closed loop identification runs produced more variations in steam flow as can be seen from Figs. 4.7 and 4.8. It can also be seen

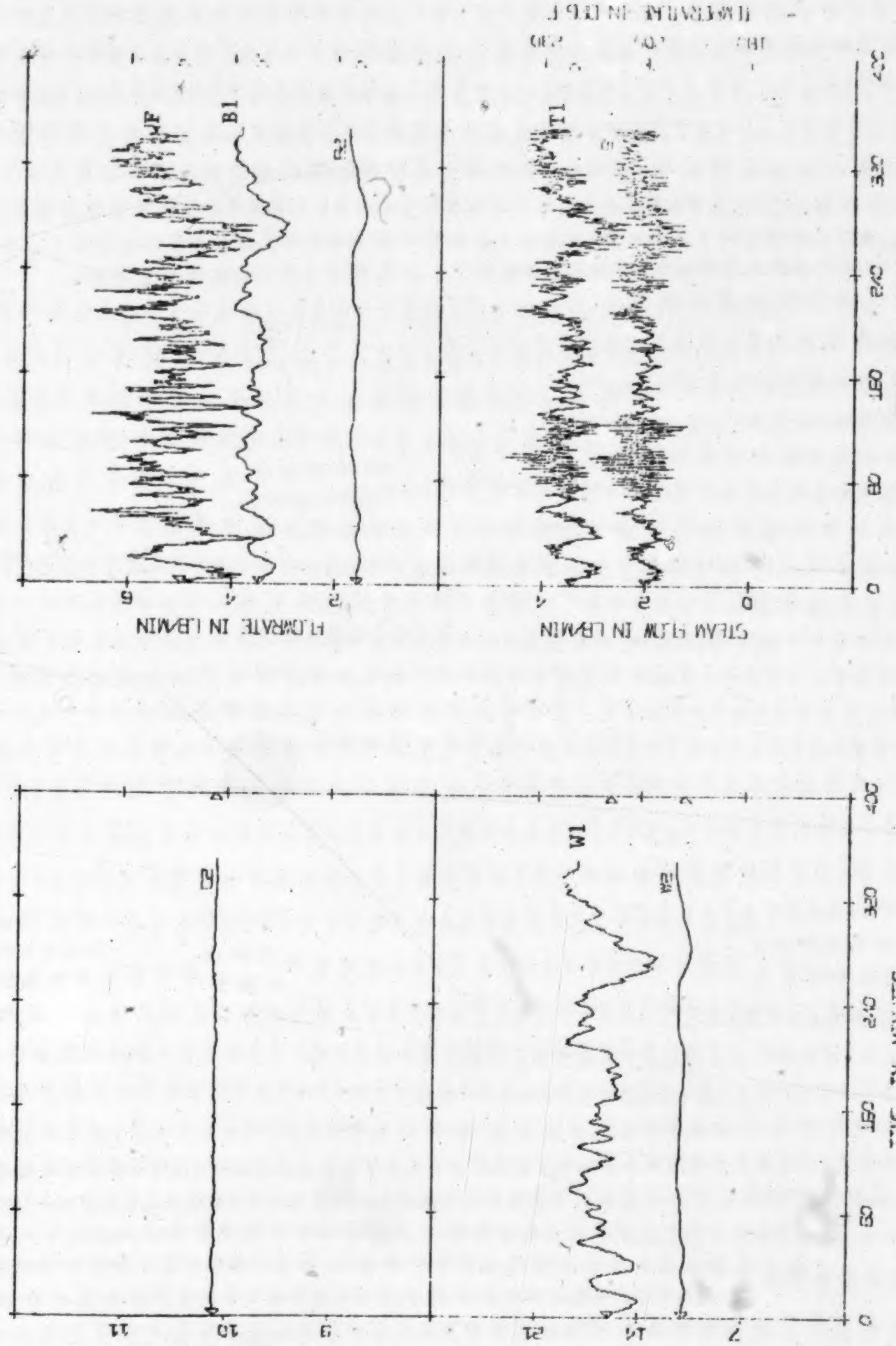


FIGURE 4.7 SIMULATION RUN SFD-3 : MMSE CONTROLLER #5

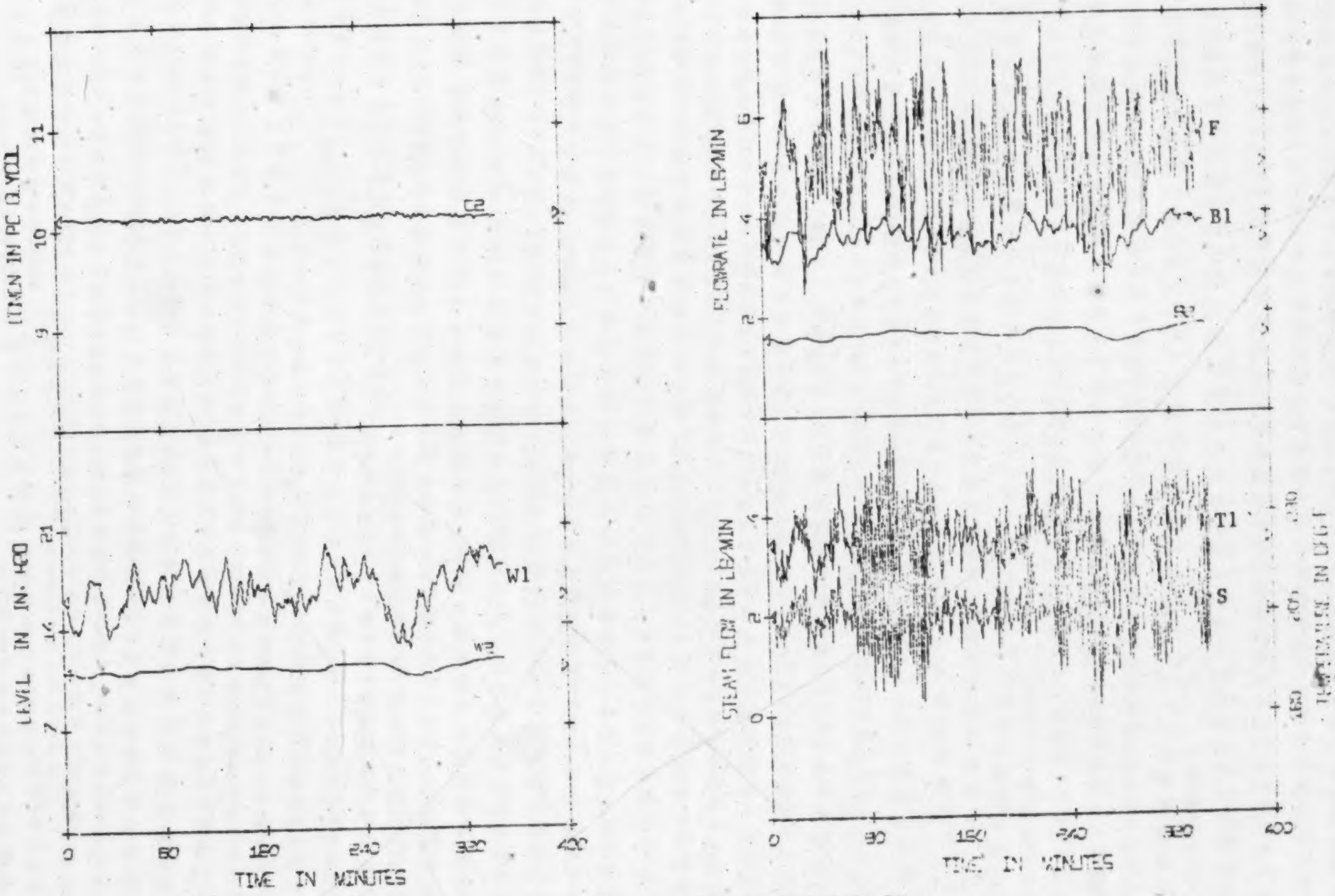


FIGURE 4.8 SIMULATION RUN SFD-4 : MMSE CONTROLLER #5

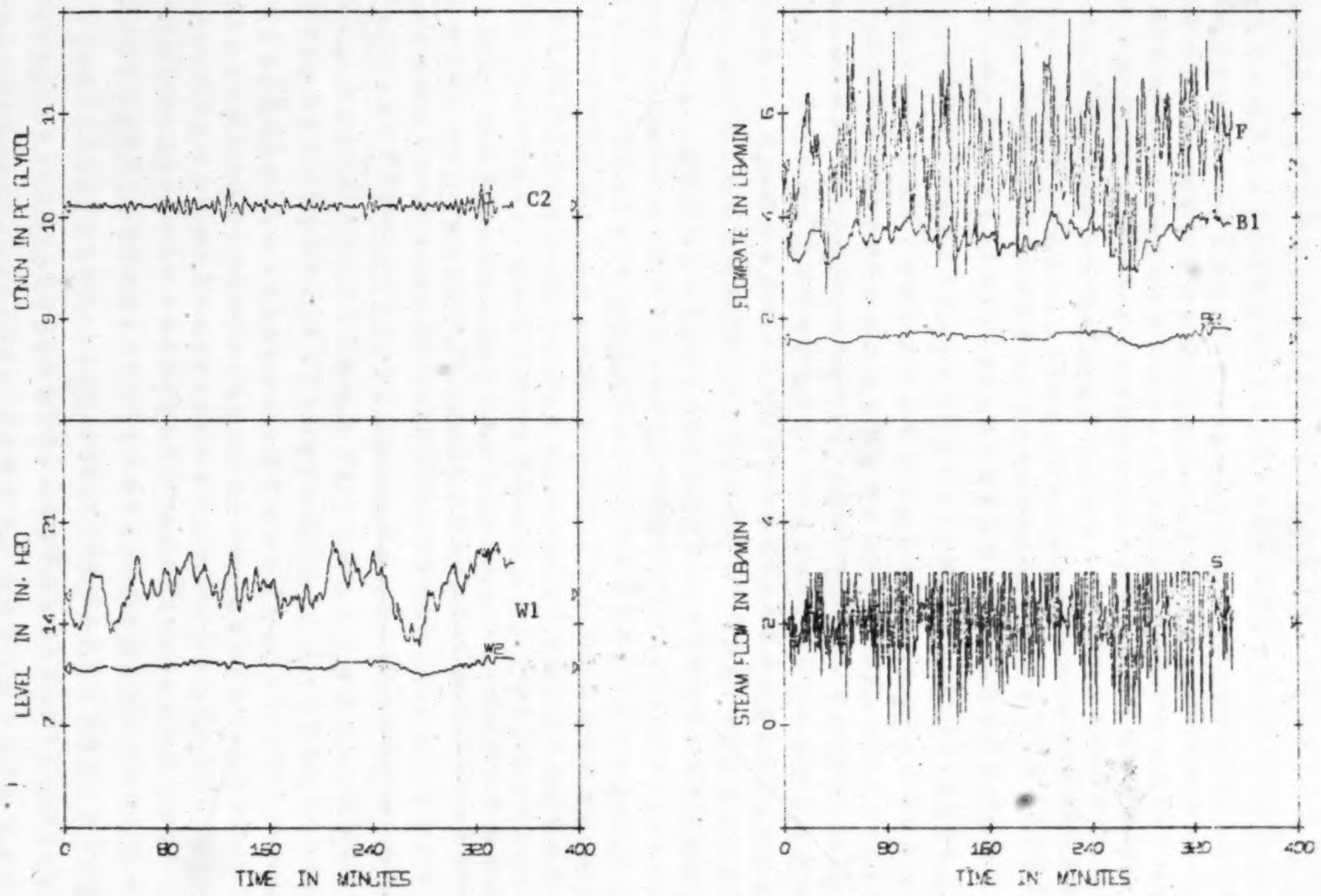


FIGURE 4.9 SIMULATION RUN SFD-4 : MMSE CONTROLLER #4

from Table 4.2 that controller PI (sim) produced a standard deviation which is 60% lower than that for the PI (exp) controller tuned by King and McNeill [23].

4.2.2 Performance under Deterministic Disturbances

The MMSE controllers were designed using models identified under stochastic disturbances similar to those used for runs SFD-1 to SFD-4. Hence their improvement over PI control in the presence of stochastic disturbances is not surprising. To test the robustness of these controllers for other types of disturbances, runs with step changes in feed flow rate were made. Figures 4.10 to 4.14 show typical responses for condition SFS-3. From Table 4.2 it can be seen that the MMSE controllers performed better than PI(sim) and PI (exp) controllers for step changes as well. Here the reduction in the error standard deviation is about a factor of 3 for controllers based on runs SSF-1 and SSF-2 and as much as 20 times for the controller based on run SSF-3. The results clearly indicate that ability of the MMSE controllers to handle deterministic disturbances as well as stochastic disturbances. One of the MMSE controllers (#7) based on closed loop runs, produced higher standard deviation than that for PI controllers. Its response shows a steady increase in the deviation of product concentration from setpoint value, indicating unstable behaviour.

TABLE 4.2

PERFORMANCE OF CONTROLLERS IN TABLE 4.1 : SIMULATION RESULTS

(Levels under Proportional Control, using Matrix $\underline{\underline{K}}_1$)

Run	Feed (lb /min)			σ_{C2}(% Glycol) MMSE CONTROLLERS									
	σ_{input}	ϕ_F	σ_F	Open Loop	PI (sim)	PI (exp)	#1	#2	#3	#4	#5	#6	#7
SFD-1	0.50	0.50	0.55	0.421	0.020	0.050	0.008	0.010	0.008	0.028	0.007	0.009	0.014
SFD-2	0.50	0.75	0.75	0.820	0.026	0.085	0.011	0.013	0.007	0.029	0.010	0.016	0.025
SFD-3	0.75	0.75	1.10	1.229	0.039	0.128	0.016	0.019	0.011	0.032	0.015	0.024	0.038
SFD-4	1.00	0.50	1.10	0.844	0.040	0.101	0.016	0.019	0.016	0.049	0.015	0.019	0.029

Run	± Step Changes in Feed (lb /min)	σ_{C2}(% Glycol) MMSE CONTROLLERS									
		Open Loop	PI (sim)	PI (exp)	#1	#2	#3	#4	#5	#6	#7
SFS-1	0.50	1.600	0.013	0.032	0.0042	0.0033	0.0006	0.018	0.007	0.008	0.14
SFS-2	0.75	2.400	0.020	0.048	0.0063	0.005	0.0009	0.017	0.010	0.012	0.21
SFS-3	1.00	3.200	0.027	0.064	0.0083	0.0066	0.0011	0.016	0.014	0.016	0.27

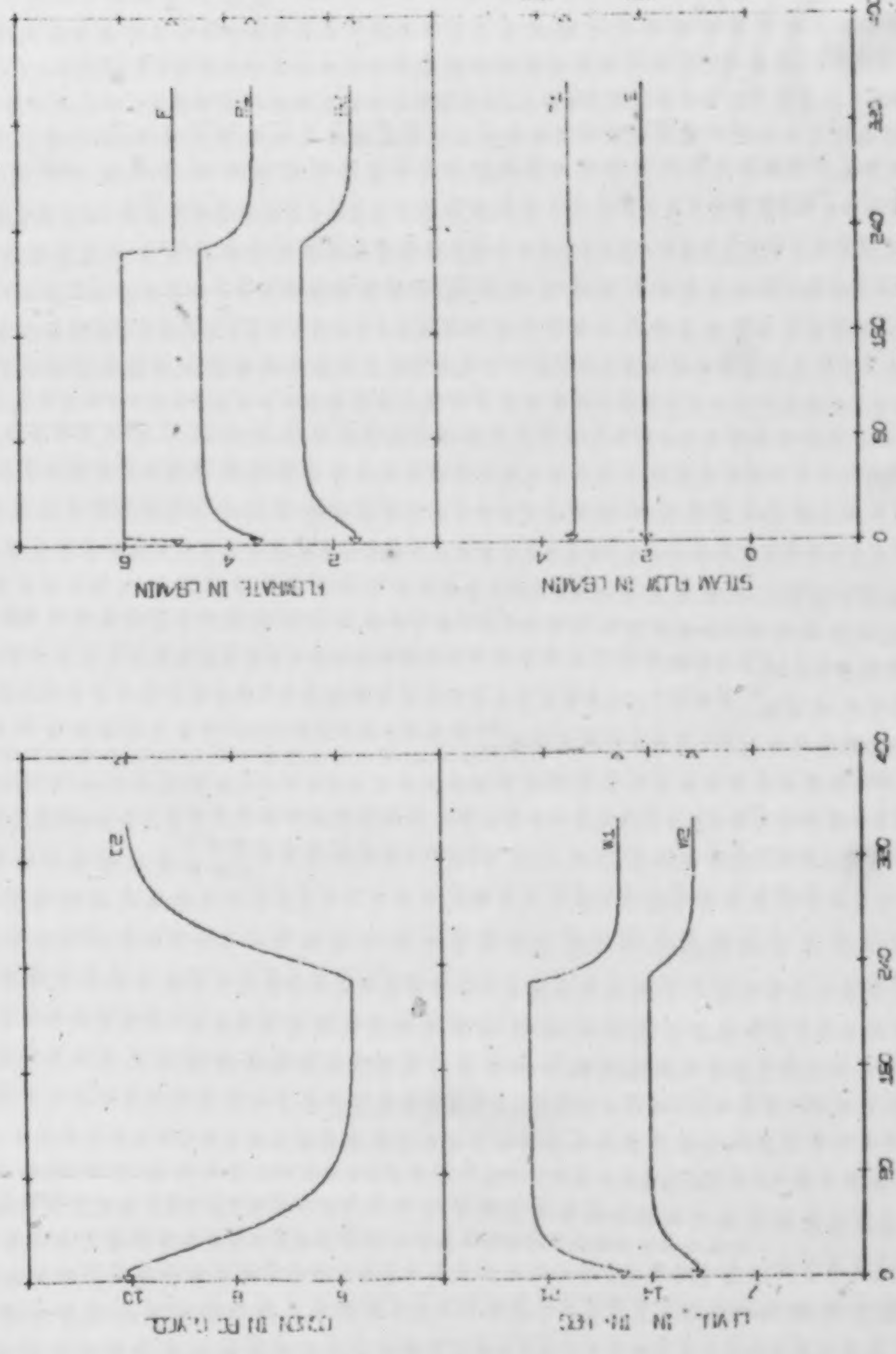


FIGURE 4.10 SIMULATION RUN SPS-3 : OPEN LOOP

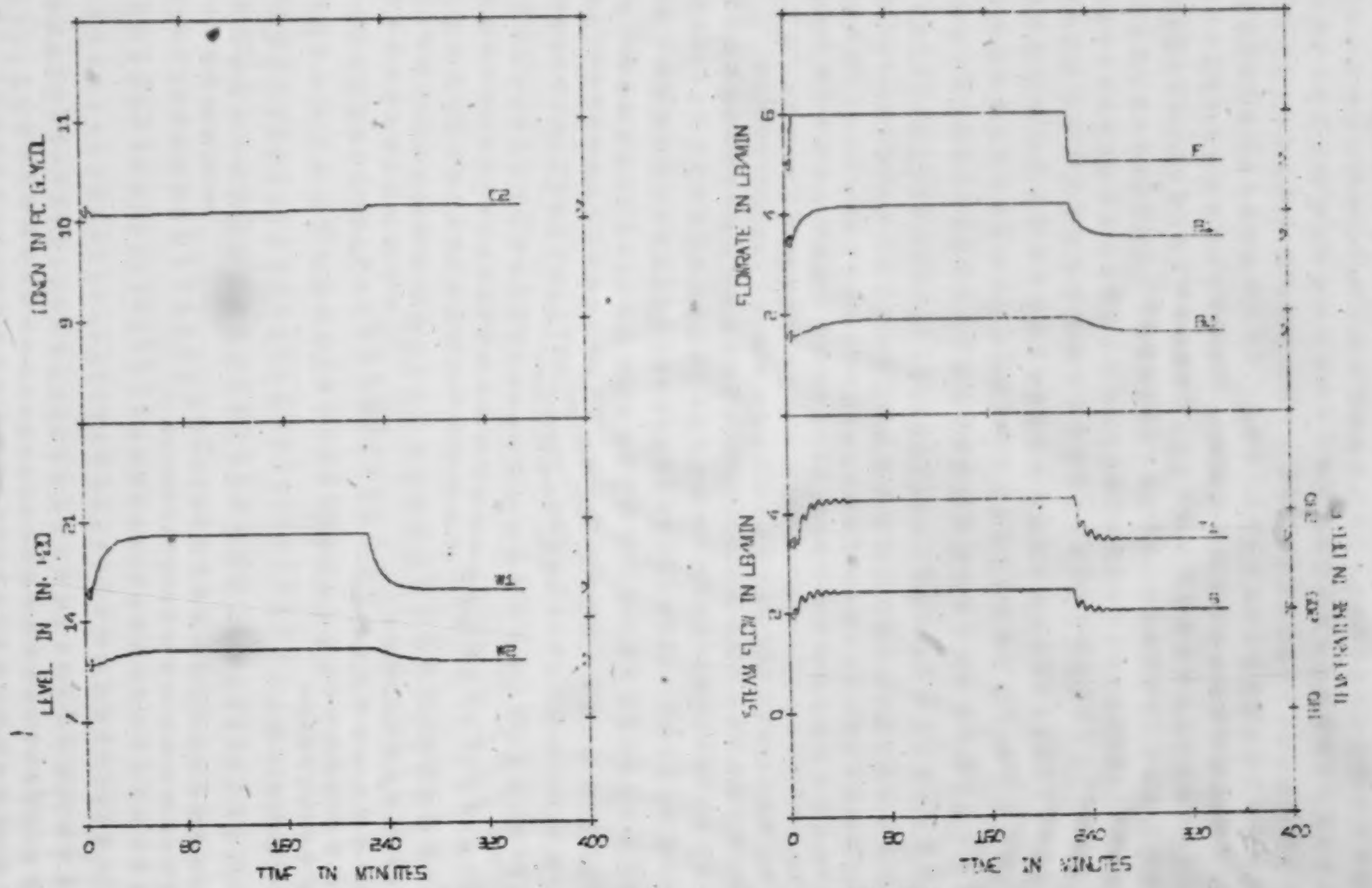


FIGURE 4.11 SIMULATION RUN SFS-3 : PI(sim) CONTROLLER

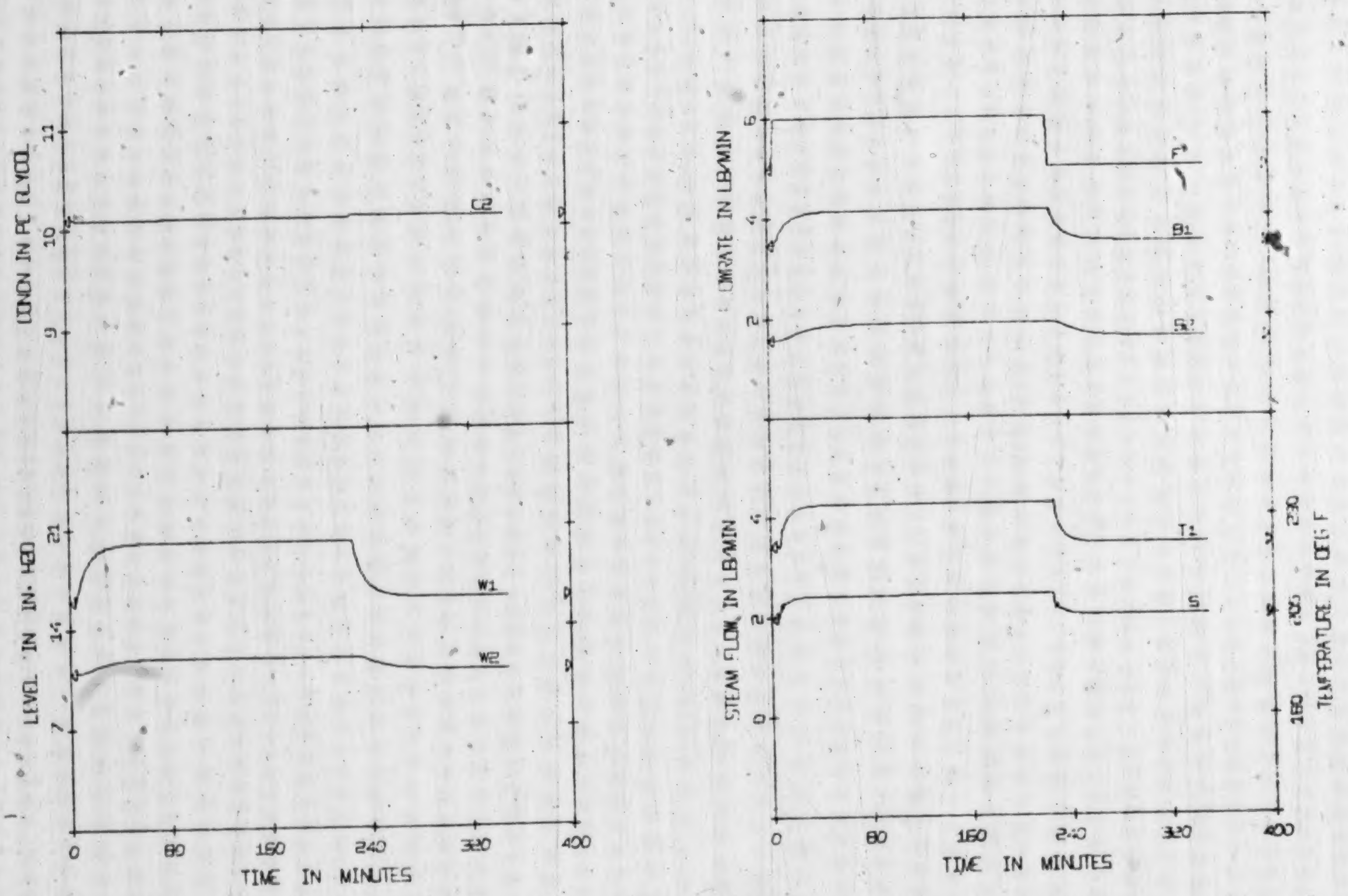


FIGURE 4.12 SIMULATION RUN SFS-3 : MISE CONTROLLER #2

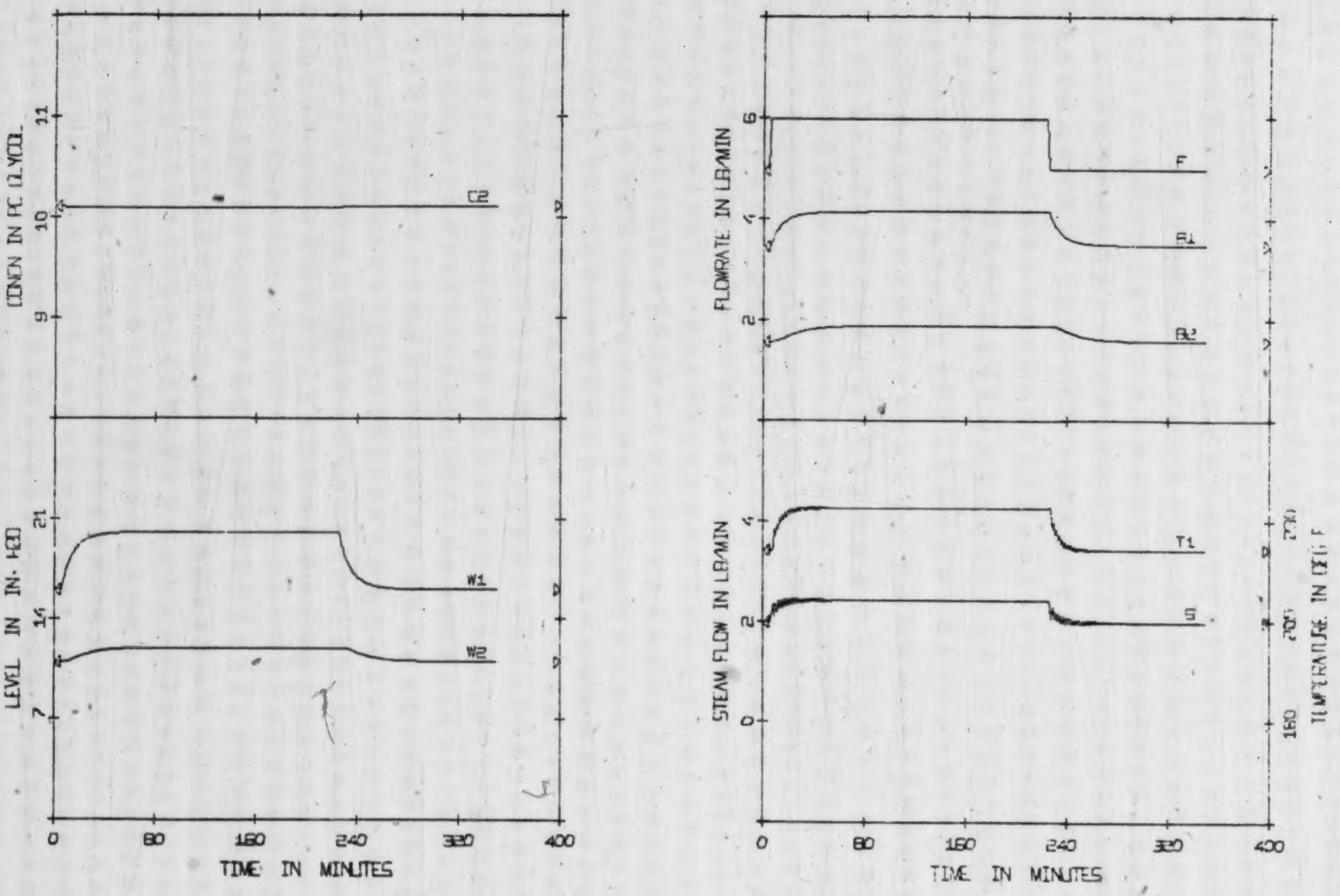


FIGURE 4.13 SIMULATION RUN SFS-3 : MMSE CONTROLLER #5

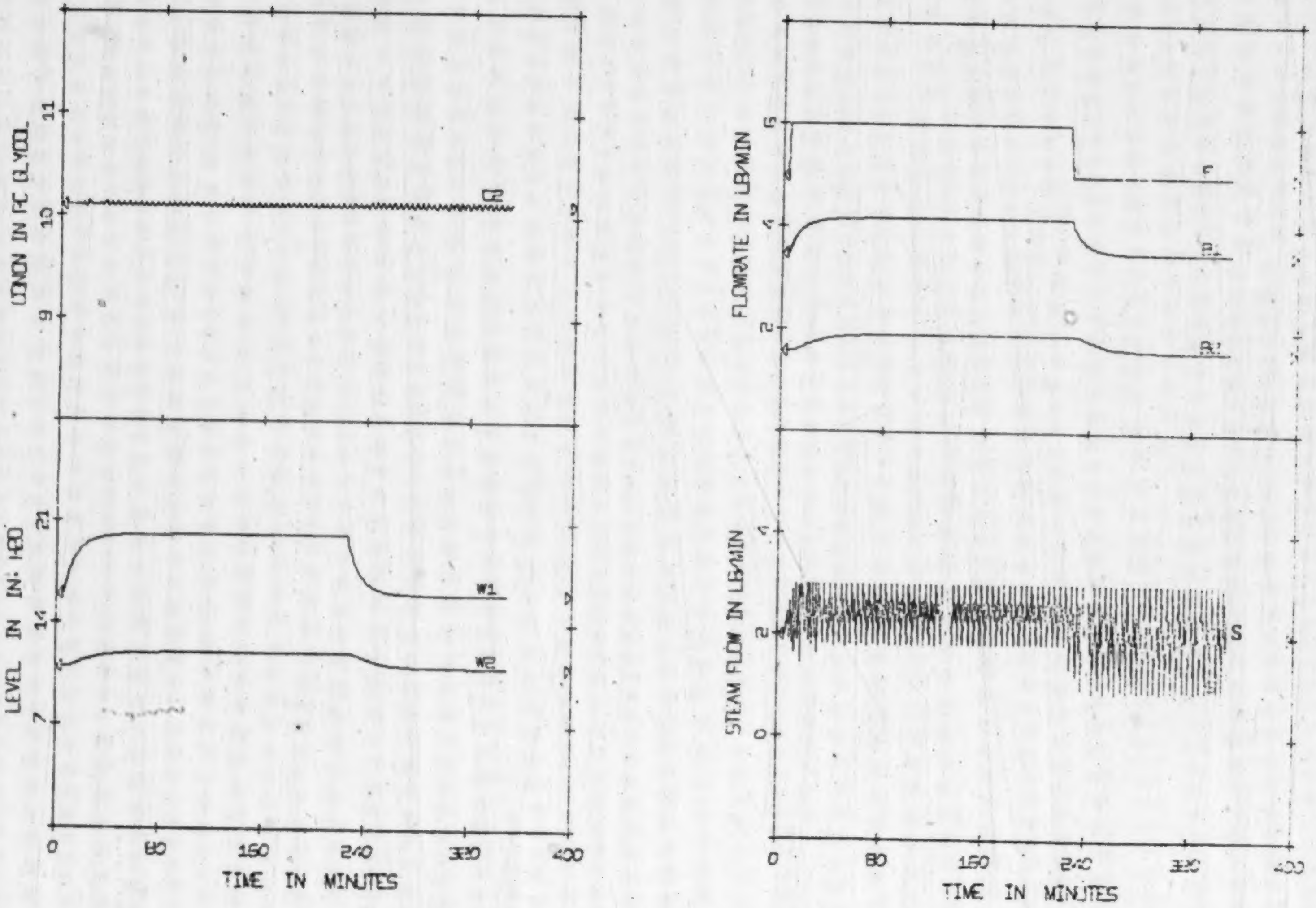


FIGURE 4.14 SIMULATION RUN SFS-3 : MMSE CONTROLLER #4

4.2.3 Performance under Setpoint Changes

The previous study of MMSE controllers indicates that they perform better than PI controllers (in the sense of minimizing sum of squares of errors), when the problem is one of regulatory control. In order to further evaluate their performance, setpoint changes were also considered. In these runs a 1 percent setpoint change was introduced at the 30th sampling interval and the standard deviations of errors produced by typical MMSE controller (#2) and PI (sim) controller were compared. Two types of responses were simulated for comparison: For the first run, feed disturbances were absent and in the second, a feed disturbance (σ_F = 0.75 lb/min, ϕ_F = 0.75) was present. Typical results are presented in Figs. 4.15 and 4.16.

The standard deviations of errors are shown below:

Run	Feed (lb/min) σ_F	Concentration (% glycol) σ_{C2}	
		PI (sim)	MMSE #2
SSP-1	0	0.08896	0.1002
SSP-2	0.75	0.08813	0.09926

Figure 4.16 shows that MMSE controller #2 produced a stable response and from the above σ_{C2} values, it is obvious that the error standard deviation is only 10 percent larger than for well-tuned PI (sim) controllers. This study suggests that MMSE controllers can also be used successfully for setpoint changes.

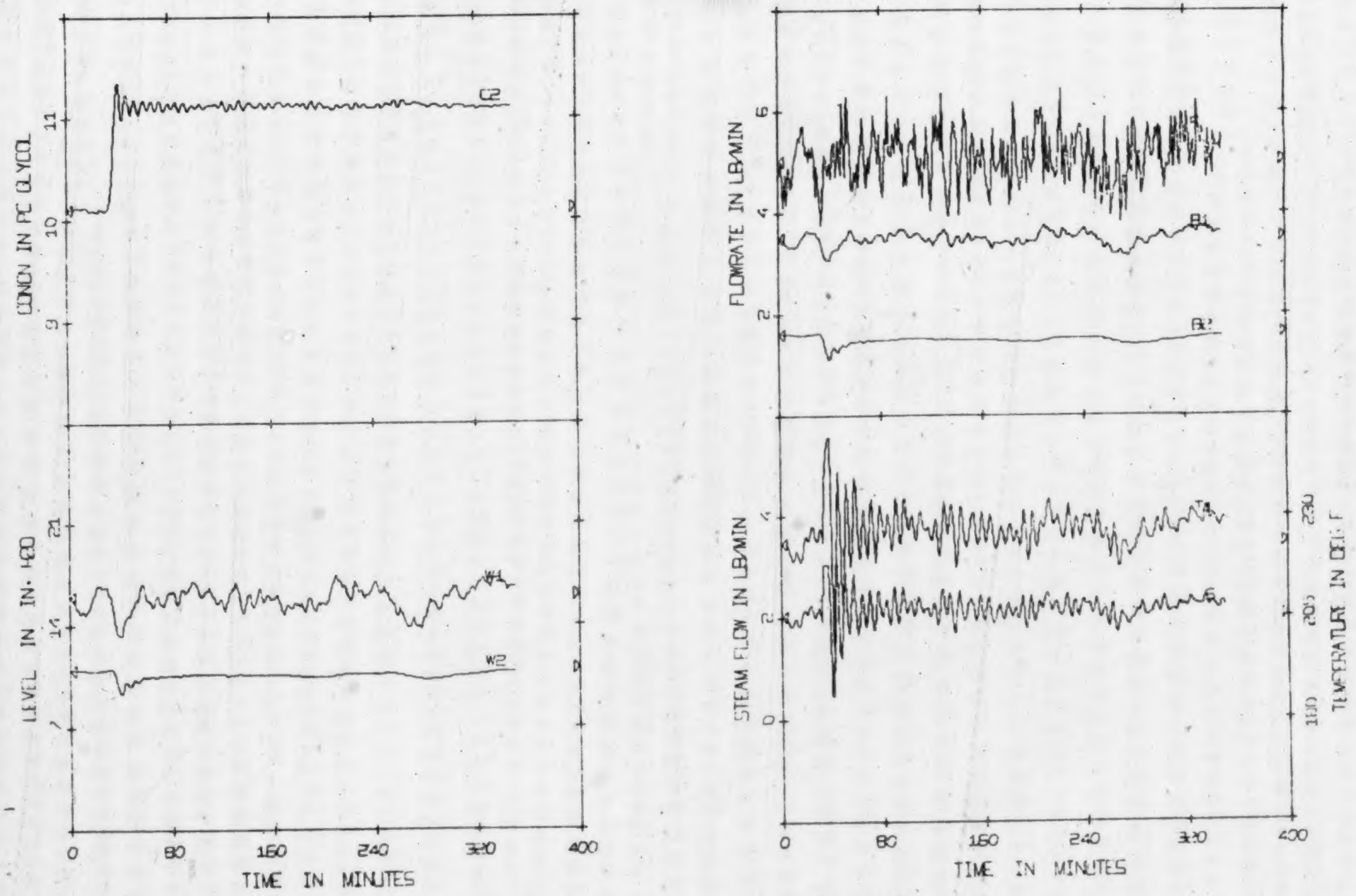


FIGURE 4.15 SIMULATION RUN SSP-2 : PI (sim) CONTROLLER

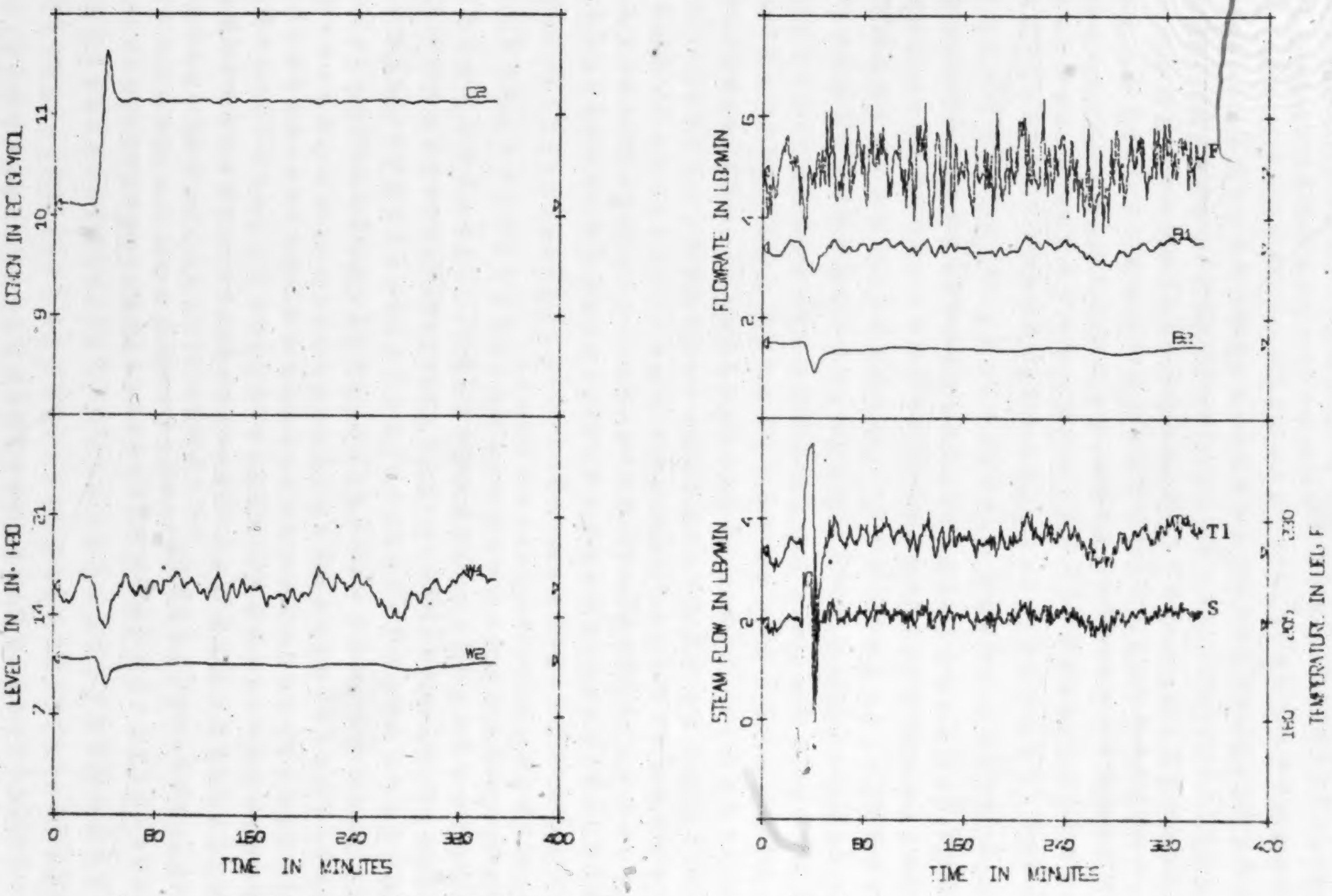


FIGURE 4.16 SIMULATION RUN SSP-2 : MMSE CONTROLLER #2

4.3 Evaluation of MMSE Controllers : Experimental Study

Minimum Mean Square Error controllers were designed, based on open loop experiments SF-1, 3 and 4. Since the noise models for these runs had a factor of (1 - B) in the denominator, these controllers include integral action. These MMSE controllers produced large input adjustments, hence some tuning was required before these controllers could be successfully implemented. In this section the required modifications and the controller performance are discussed and comparisons are made with the well tuned PI controller reported by King and McNeill [23]. As in the simulation study, both stochastic and deterministic load disturbances were employed.

4.3.1 Implementation of MMSE Controllers

The output signal of a MMSE controller is calculated as a weighted sum of present and past values of the error and the manipulated variable. These controllers were implemented using the newly added "Z-transform" controller option in the Direct Digital Control (DDC) package [24] available on the Department's IBM-1800 computer [25]. This alogorithm provides storage for one gain term with four weighting parameters for past values of errors and four for past values of the manipulated variable. Control was implemented by cascading the "Z-transform control" loop with steam flow control loop. Further details of the implementation are discussed in a research report by Kogekar and Berka [24].

The levels W1 and W2, were under proportional control using controller $\underline{\underline{K}}_1$ (eqn. 3.7). Level control and data acquisition for the experimental runs were carried out employing the multivariable

TABLE 4.3

MMSE AND MODIFIED STOCHASTIC CONTROLLERS DESIGNED USING MODELS FROM EXPERIMENTAL OPEN-LOOP IDENTIFICATION

MMSE Controller

$$C(B) = K\ C_o(B)$$

Modified Stochastic Controller,

$$C'(B) = K'\ C_o(B)$$

No.	Run No.	K	K'	$C_o(B)$
1	SF-1	103.05	40.66	$\frac{(1 - 1.8810\ B + 1.0118\ B^2 - 0.1274\ B^3)}{(1 - 1.4080\ B + 0.4494\ B^2 - 0.0413\ B^3)}$
2	SF-3	131.55	40.66	$\frac{1 - 1.8845\ B + 1.0187\ B^2 - 0.1301\ B^3}{1 - 1.0023\ B - 0.0484\ B^2 + 0.0507\ B^3}$
3	SF-4	230.38	40.66	$\frac{1 - 1.9524\ B + 1.1341\ B^2 - 0.1779\ B^3}{1 - 1.3874\ B + 0.2932\ B^2 + 0.0942\ B^3}$

control and identification programs developed previously for the evaporator system [26].

4.3.2 The Modified Stochastic Controllers

Table 4.3 presents the minimum mean square error controllers designed for open loop identification runs SF-1, 3 and 4. In each experimental run, the MMSE controller was initiated after the evaporator had attained the nominal steady state. However, even before the feed disturbances were introduced it was observed that for very small deviations in the product concentration (of the order of 0.01 - 0.02%) the steam flow rate manipulations were very large, reaching the upper and lower physical constraints quite frequently. Instead of reducing the output deviations from the setpoint value, the controllers produced an unstable condition. Hence it was necessary to modify the MMSE controllers in order to reduce the variations in the manipulated variable and avoid excessive corrective action for small deviations of the concentration. This was done by lowering the value of gain, K, by fifty percent or more, of the value obtained for MMSE controller. (The "gain" is defined by the expression in Table 4.3). The reduced "gain" values, K', are also presented in Table 4.3. These values were obtained by reducing the "gain" in successive steps until adequate control, in absence of feed disturbances, was achieved. Thus for the modified stochastic controllers in Table 4.3, all the parameter values other than the "gain" K, have the same numerical values as the original MMSE controller parameters.

The identified evaporator models have a root near the unit circle (e.g. for run SF-4 the roots are 1.018, 1.393). This means

TABLE 4.4

EXPERIMENTAL CONTROL RUNS

(Level Control Using Control Matrix $\underline{K}_1$)

Run No.	Fig. No.	Feed (lb /min)			Steam (lb./min)	Concentration (% Glycol)			Controller
		σ_{input}	ϕ_F	σ_F	σ_s	mean	setpoint	σ_{C2}	
FD-11	4.19	0.25	0.75	0.36	0.12	9.87	9.88	0.061	PI
FD-12	4.20	0.25	0.75	0.35	0.17	9.70	9.70	0.033	#1
FD-13	4.21	0.25	0.75	0.35	0.18	9.57	9.56	0.041	#2
FD-20	4.22	0.35	0.75	0.50	0	9.85	-	0.387	Open Loop
FD-21	4.23	0.35	0.75	0.49	0.14	10.44	10.43	0.082	PI
FD-22	4.24	0.35	0.75	0.51	0.20	9.73	9.76	0.055	#1
FD-23	4.25	0.35	0.75	0.49	0.15	9.69	9.70	0.053	#2
FD-24	4.26	0.35	0.75	0.49	0.23	9.99	10.00	0.075	#3
		-20% Step Change				New s.s. Value			
FS-11	4.27	-	-	0.012	0.15	9.46	9.43	0.068	PI
FS-12	4.28	-	-	0.012	0.19	9.82	9.76	0.031	#1
FS-13	4.29	-	-	0.012	0.15	9.28	9.20	0.051	#2
FS-14	4.30	-	-	0.012	0.31	9.18*	9.45	0.201*	#3

* Severe vacuum disturbance.

a change in the manipulated variable has little immediate effect on the controlled variable [1, p. 472]. Therefore the MMSE controller calls for excessive input manipulations. In conditions such as this, modifying the controller is recommended [1, 11, 12]. The constants in the numerator polynomial $\omega(B)$ have values of the order of 10^{-3} to 10^{-4} and these values change significantly with changes in process conditions. The 95 percent confidence limits on these parameters are very wide (c.f. Appendix D). The effect is that the numerator of the controller has parameters of the order of 10^{3} and the "gain" K is subject to large variations with wide 95 percent confidence limits. Hence, in order to have a stable stochastic controller a reduction in the value of "gain" term was attempted.

4.3.3 Discussion of the Results

The performance of stochastic controllers obtained from various identification runs was evaluated for two stochastic (first order autoregressive) disturbances and for an approximately 20 percent step decrease in feed flow rate from 5.5 lb/min to 4.5 lb/min. The various run conditions and the standard deviations of feed flow, steam and product concentration are presented in Table 4.4 and Figs. 4.19 - 4.30.

During the experimental control runs, periodic fluctuations in the building vacuum supply were observed. In order to ensure that these fluctuations were external to the evaporator apparatus, the building vacuum supply was also recorded in the Department's Instrument Shop and is presented in Fig. 4.17. Approximately every 100 minutes there was a sudden drop in the vacuum from -21.3 inch Hg to -20.3 inch,

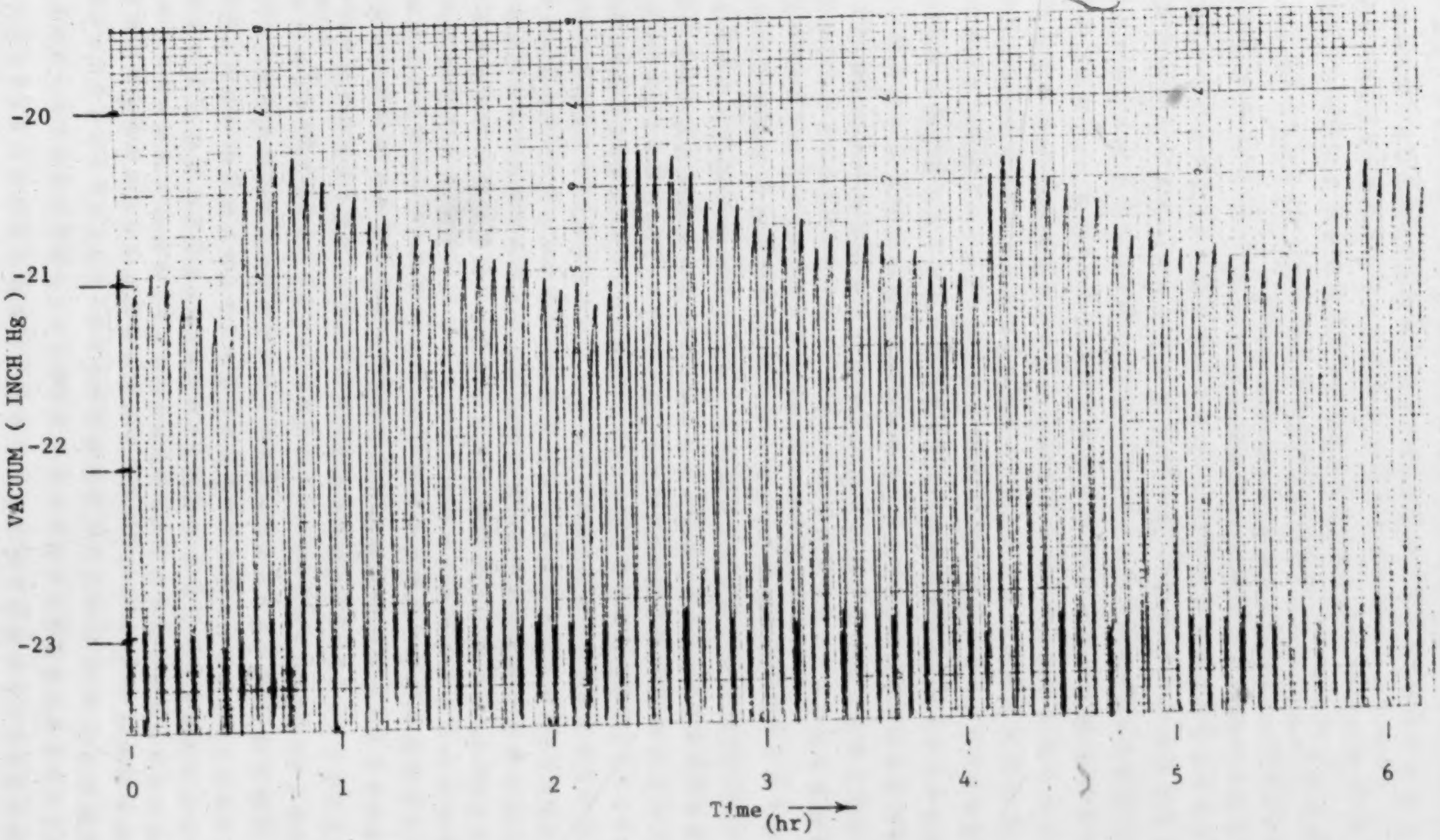


FIGURE 4.17 CHART RECORD OF BUILDING VACUUM SUPPLY PRESSURE.

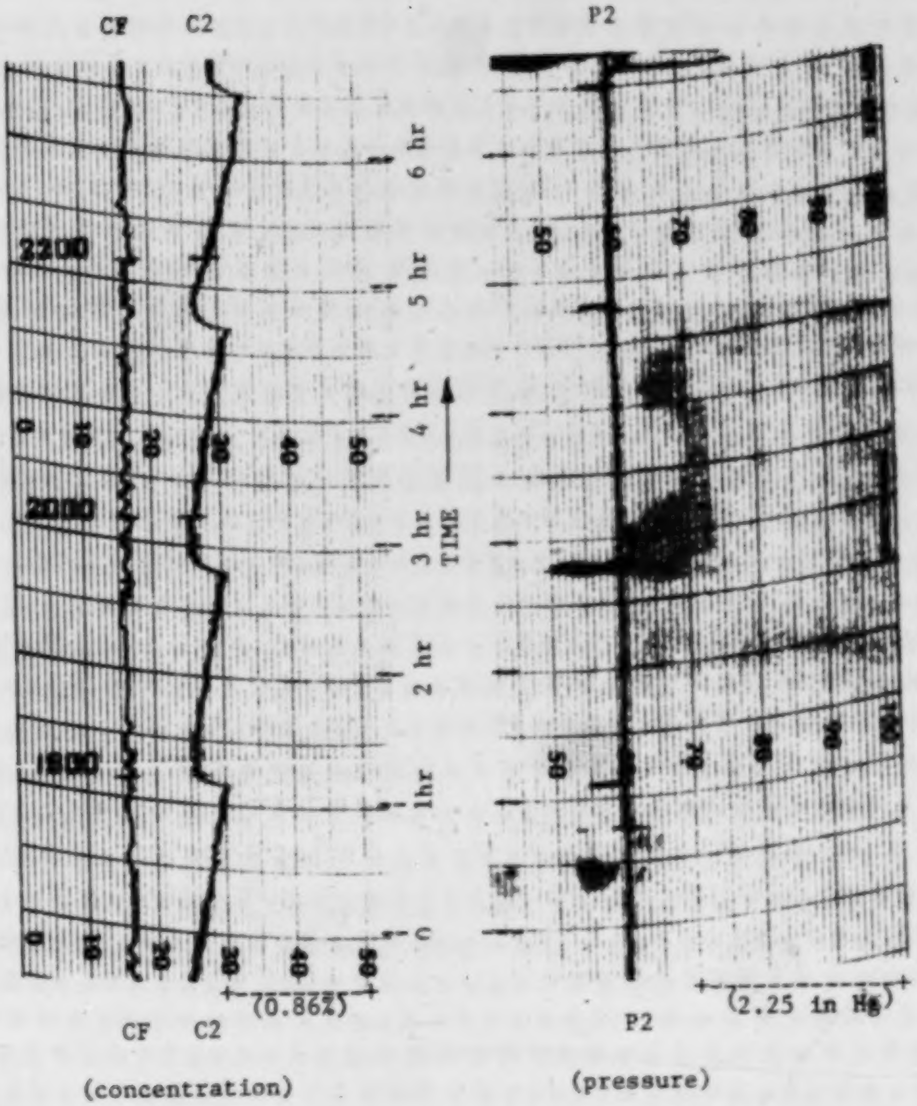


FIGURE 4.18 EFFECT OF VACUUM DISTURBANCES ON PRODUCT CONCENTRATION

then the vacuum slowly increased back to -21.3 inch during the next 100 minutes. In the evaporator system, the vacuum passes through two vacuum damper tanks in series before reaching the separator. The separator pressure is controlled at a value of -18.75 inch Hg by manipulating a slip stream of air entering the separator. Even under these conditions the sudden drop in vacuum supply caused a pressure increase of approximately 0.25 - 0.50 inch Hg in the separator. Since the product concentration is very sensitive to variations in second effect pressure, P2, these periodic pressure increases caused sharp decreases in the product concentration as well as decreases in the separator level.[1] The vacuum behaviour is shown in Fig. 4.17 and its effect on concentration is illustrated in Fig. 4.18 by presenting the analog plots of product concentration and P2. (The problem with the building supply pressure was not present during the identification runs described in Chapter Three).

During the control runs these sudden decreases in concentration caused corresponding sudden increases in steam flow rate. As a result, oscillations in steam and concentration resulted and the standard deviation of errors increased. It was observed that the stochastic controllers performed poorly whenever the concentration suddenly deviated from setpoint value by more than $\frac{1}{3}$ percent glycol. For smaller changes, small offsets resulted whereas for larger deviations, unstable behaviour was observed. By contrast, the PI controller provided satisfactory control (c.f. Figs. 4.23 and 4.27).

In summary, the control would have been much better if the vacuum had remained constant and the stochastic controllers did not

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[1] *In Figs. 4.19 to 4.30 arrows indicate drop in vacuum.*

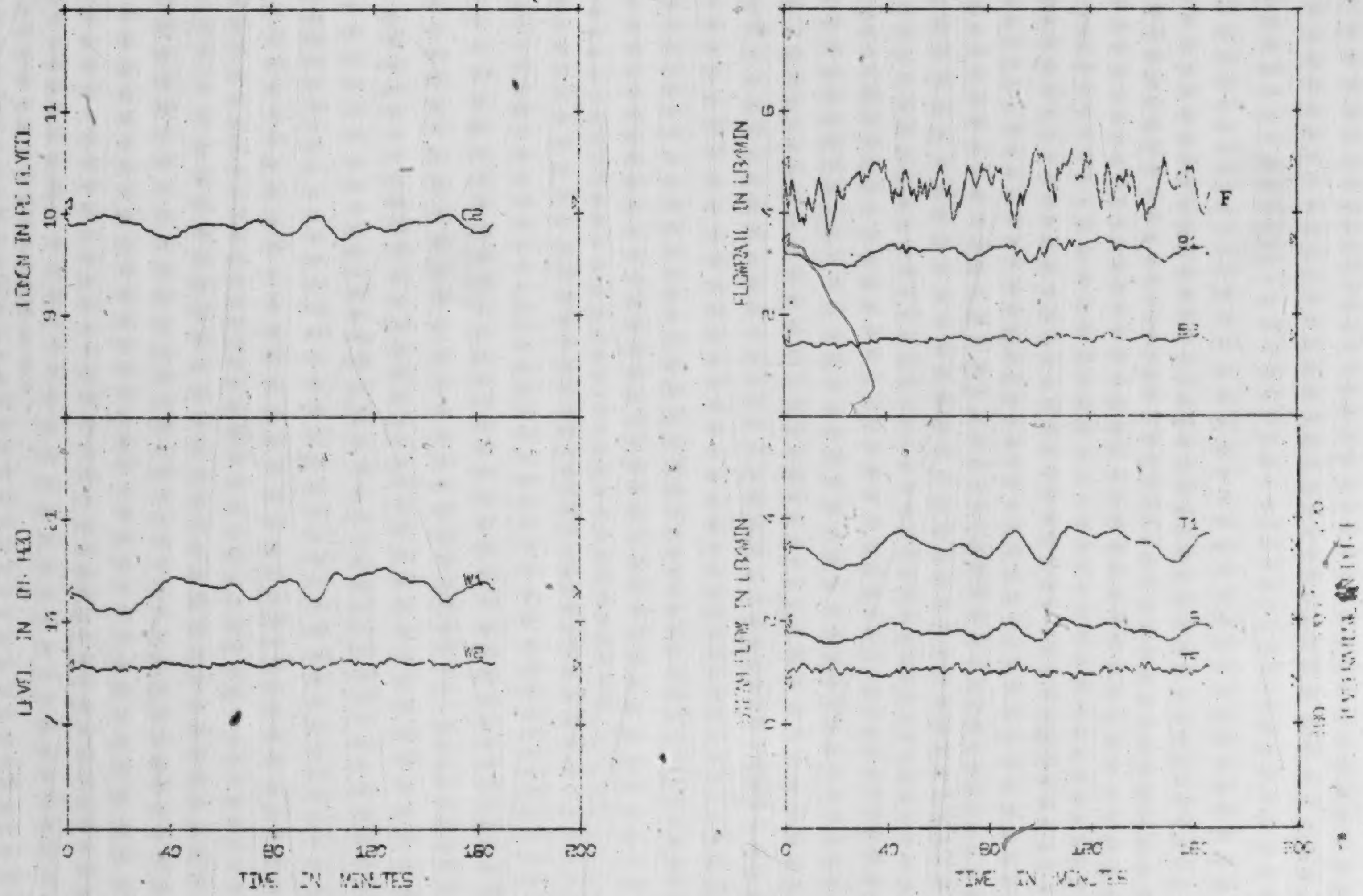

FIGURE 4.19 EXPERIMENTAL RUN FD-11 : PI CONTROLLER

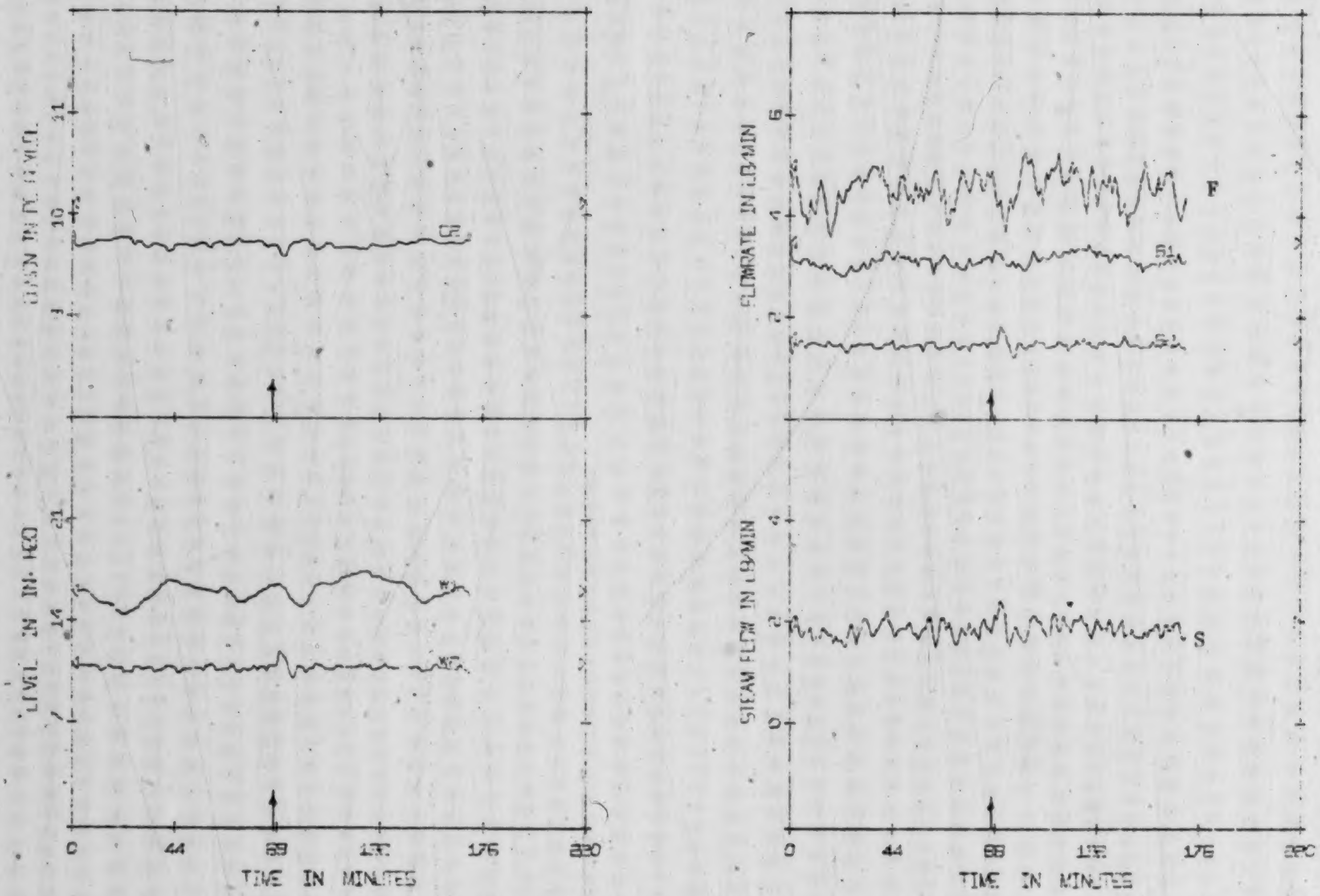

FIGURE 4.20 EXPERIMENTAL RUN FD-12 : STOCHASTIC CONTROLLER #1

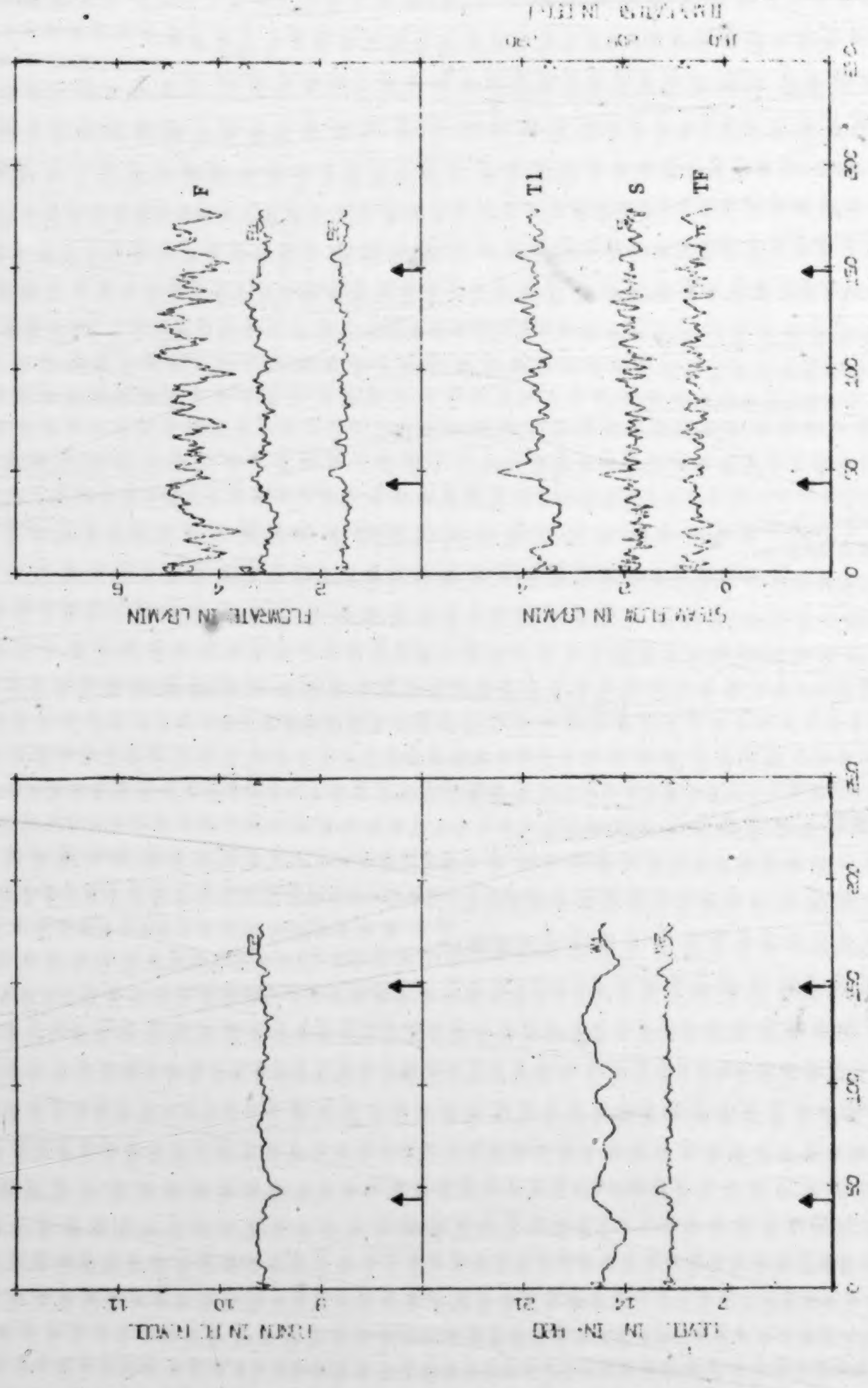

FIGURE 4.21 EXPERIMENTAL RUN FD-13 : STOCHASTIC CONTROLLER #2

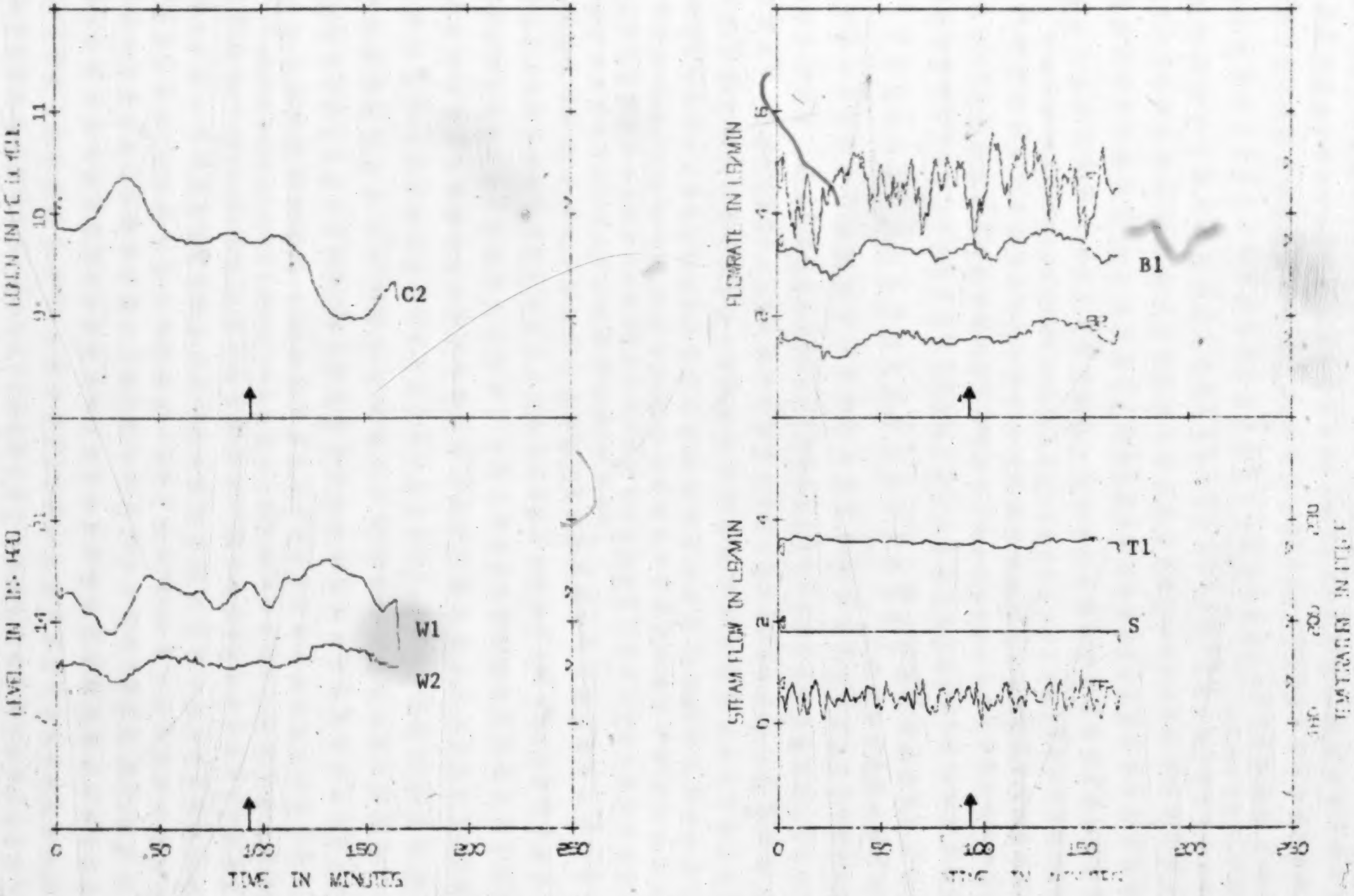

FIGURE 4.22 EXPERIMENTAL RUN FD-20 : OPEN LOOP

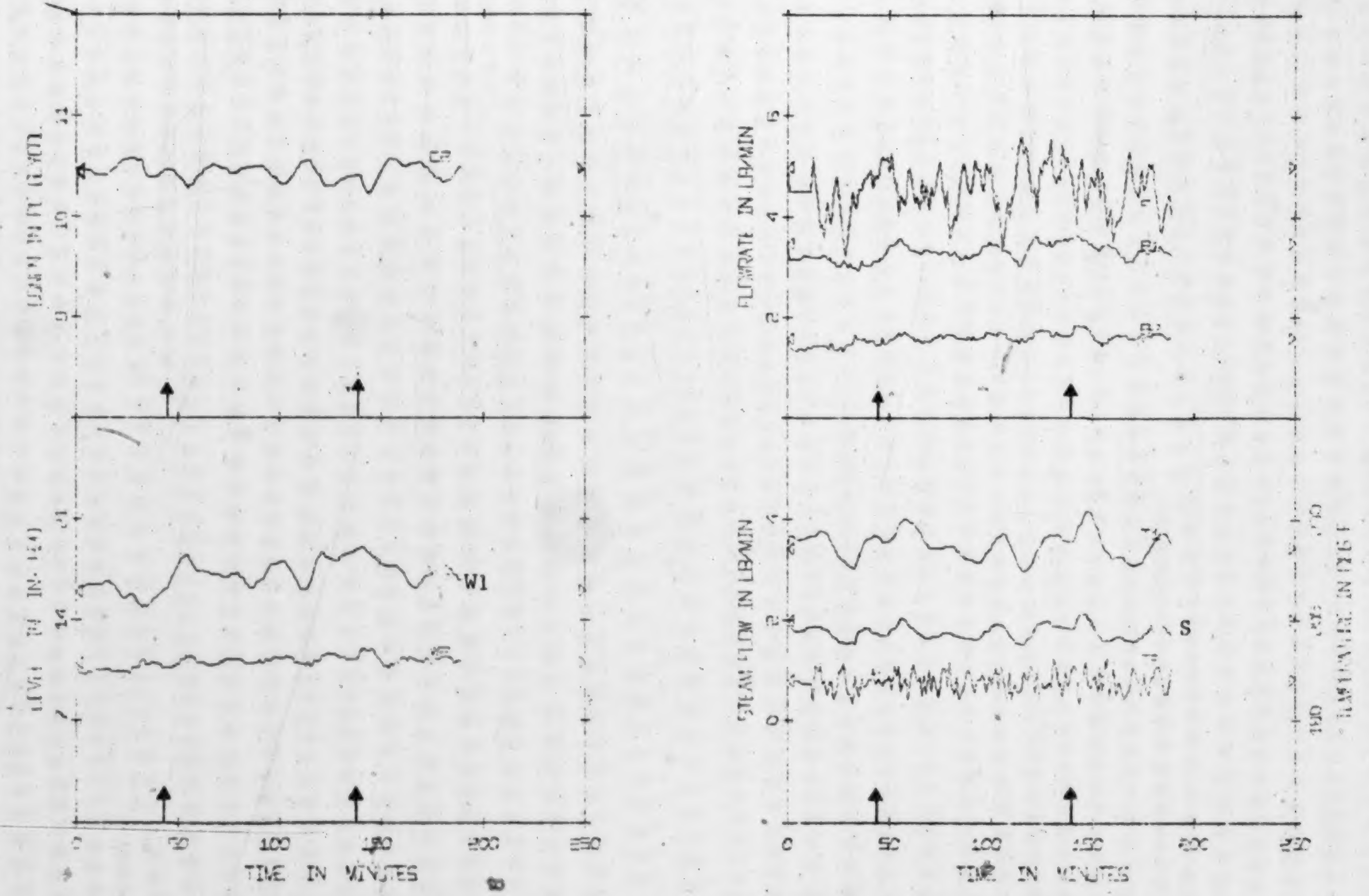

FIGURE 4.23 EXPERIMENTAL RUN FD-21 : PI CONTROLLER

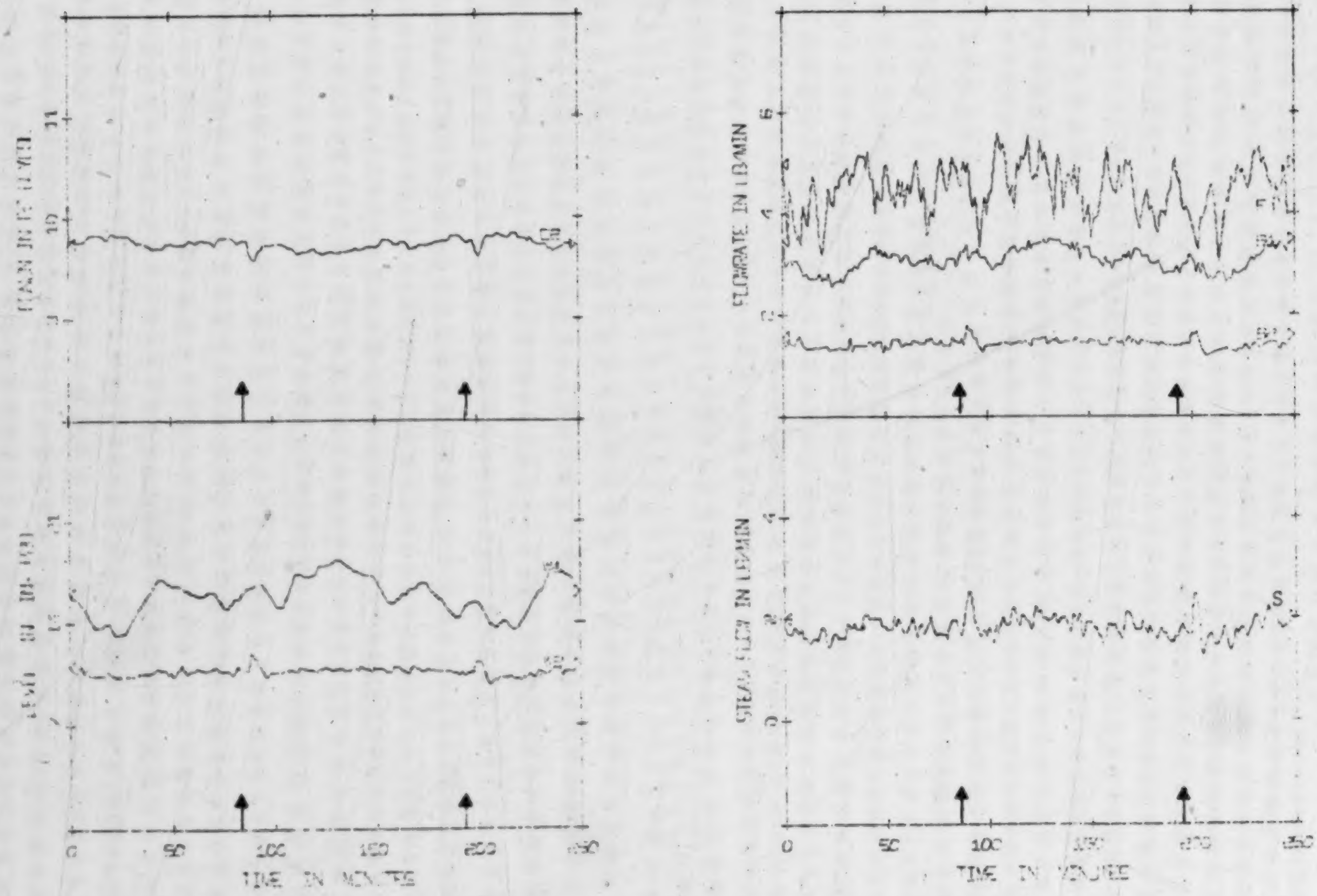

FIGURE 4.24 EXPERIMENTAL RUN FD-22 : STOCHASTIC CONTROLLER #1

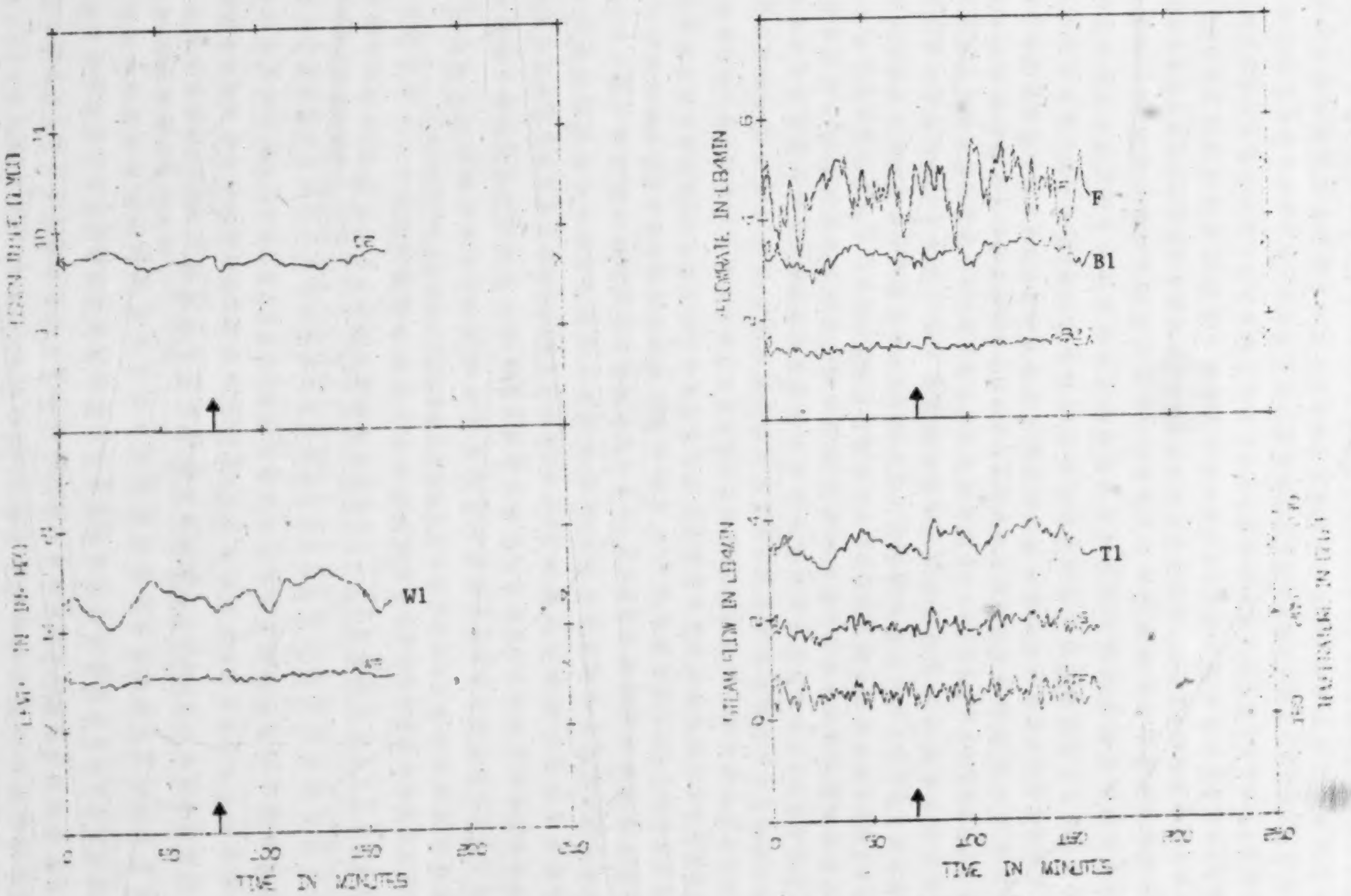

FIGURE 4.25 EXPERIMENTAL RUN FD-23 : STOCHASTIC CONTROLLER #2

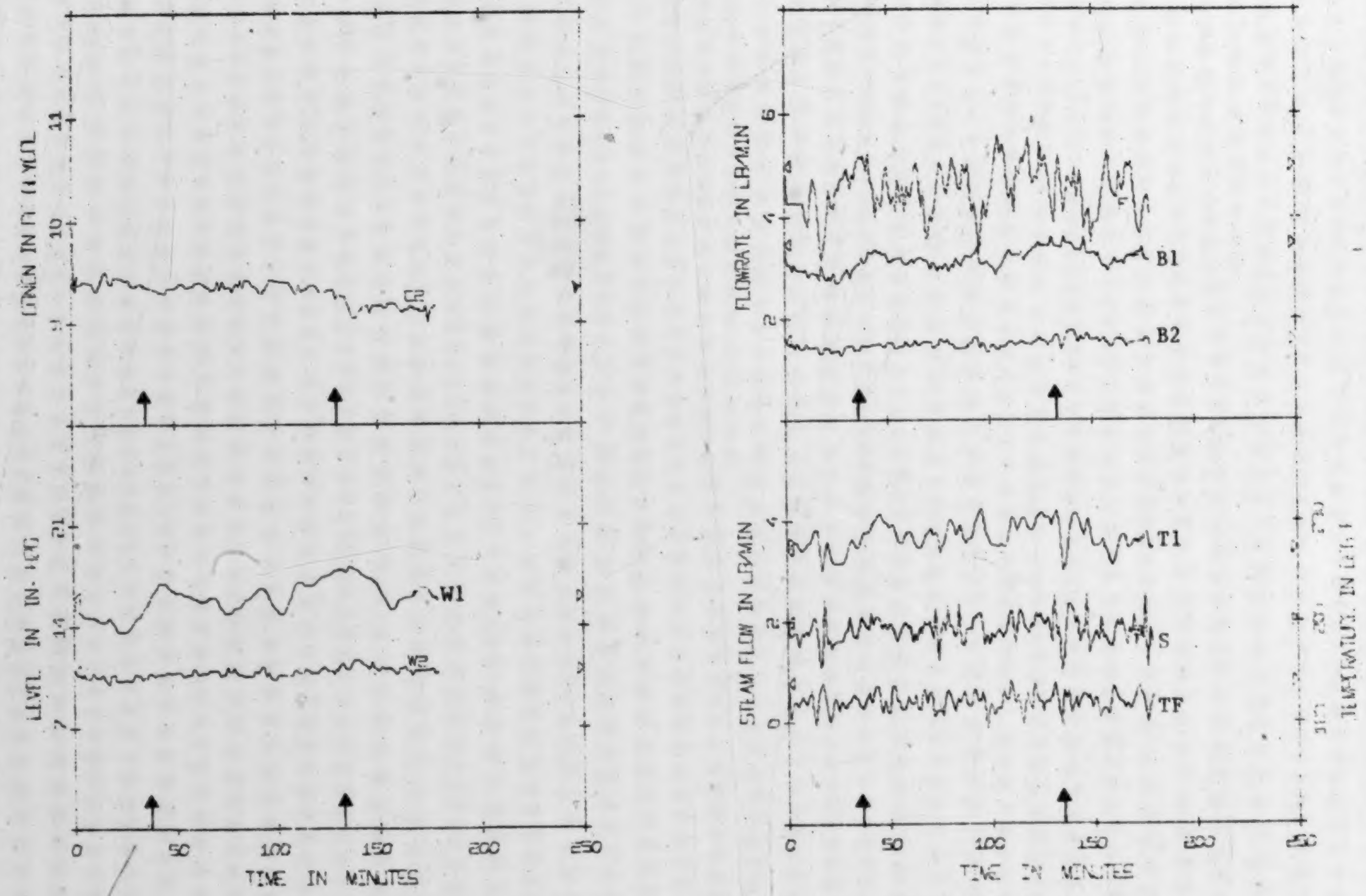

FIGURE 4.26 EXPERIMENTAL RUN FD-24 : STOCHASTIC CONTROLLER #3

prove very useful for handling these disturbances which tended to resemble setpoint changes.

Table 4.4 shows that the error standard deviation for PI or stochastic control is 4 - 7 times lower than the values for open loop (or no control). Compared to PI controllers, modified stochastic controllers produced a 10 - 50 percent reduction in standard deviation for the same flow disturbances. The mean value of the product concentration is almost the same as the setpoint indicating no offset for stochastic disturbances.

Although the standard deviation of product concentration has decreased when stochastic control is used the steam standard deviation has increased by approximately 50 percent, with the exception of run FD-23.

Runs FS-11 to FS-14 were carried out for a -20 percent step decrease in feed flow rate. The standard deviation was calculated starting form the point at which step change was introduced. Here also the standard deviations of the errors are smaller than those obtained using PI control by 10 - 50 percent, in case of runs FS-12 and FS-13. The steam standard deviations were nearly equal for runs FS-11 and FS-13 and were 25 percent more for run FS-12. Here the deviations of the mean from the setpoint are more than for stochastic disturbances.

It can be seen from Figs. 4.18 to 4.20 that the final steady state values are different from the setpoint or the initial steady state value. But the deviations did not generally begin from the time when the step change in feed flow is introduced as they were caused by the sudden changes in vacuum.

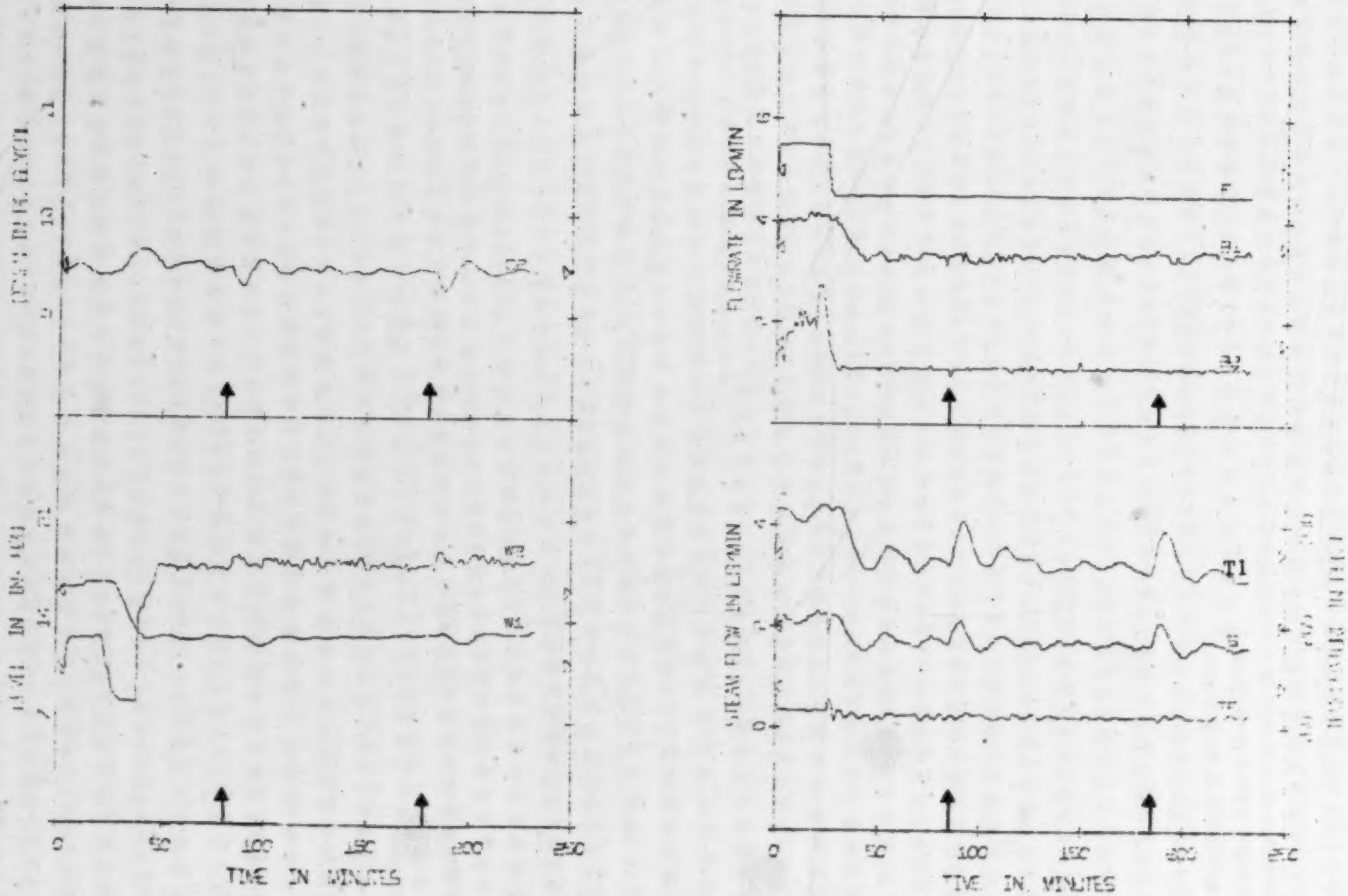

FIGURE 4.27 EXPERIMENTAL RUN FS-11 : PI CONTROLLER

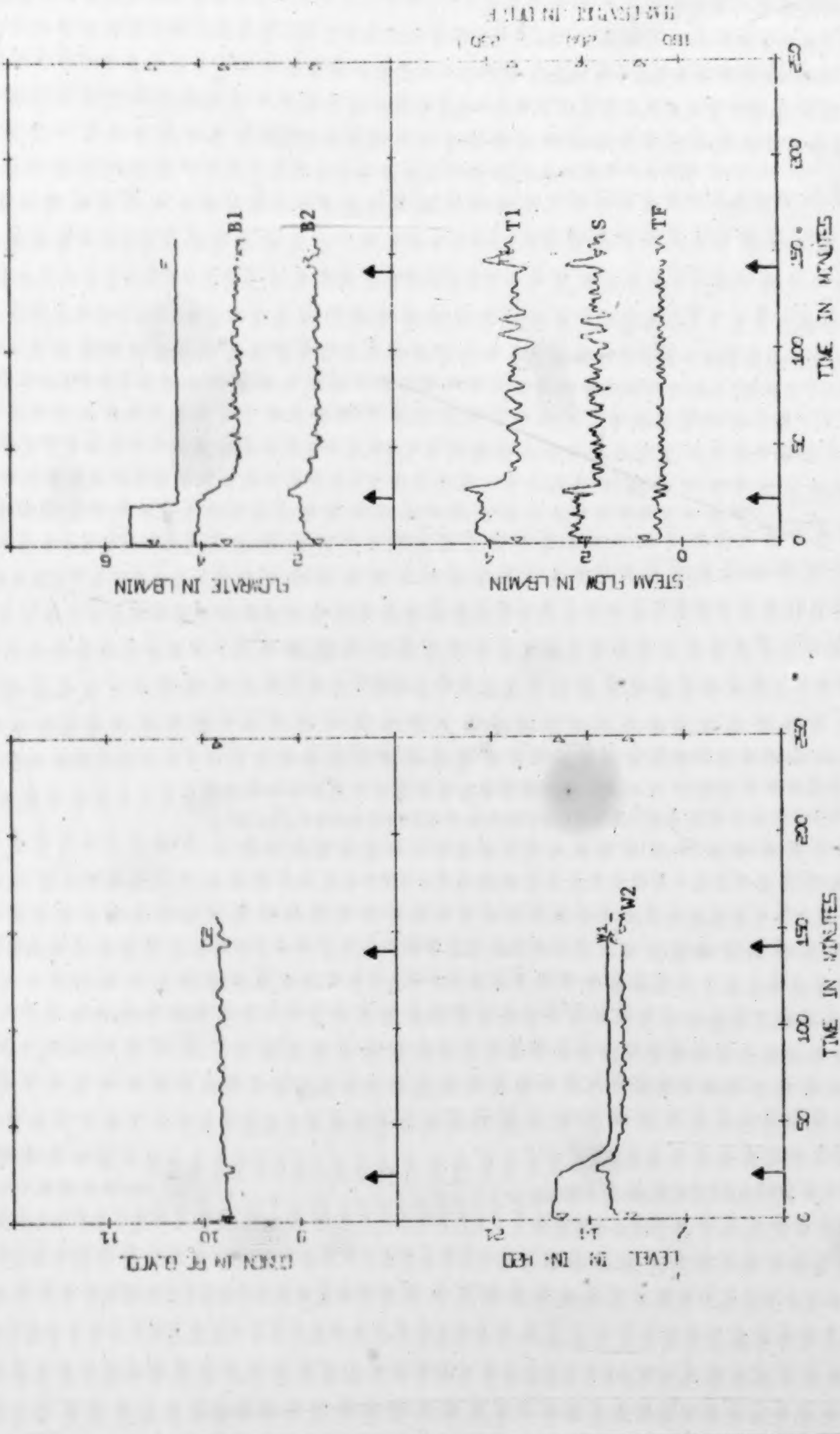

FIGURE 4.28 EXPERIMENTAL RUN FS-12 : STOCHASTIC CONTROLLER #1

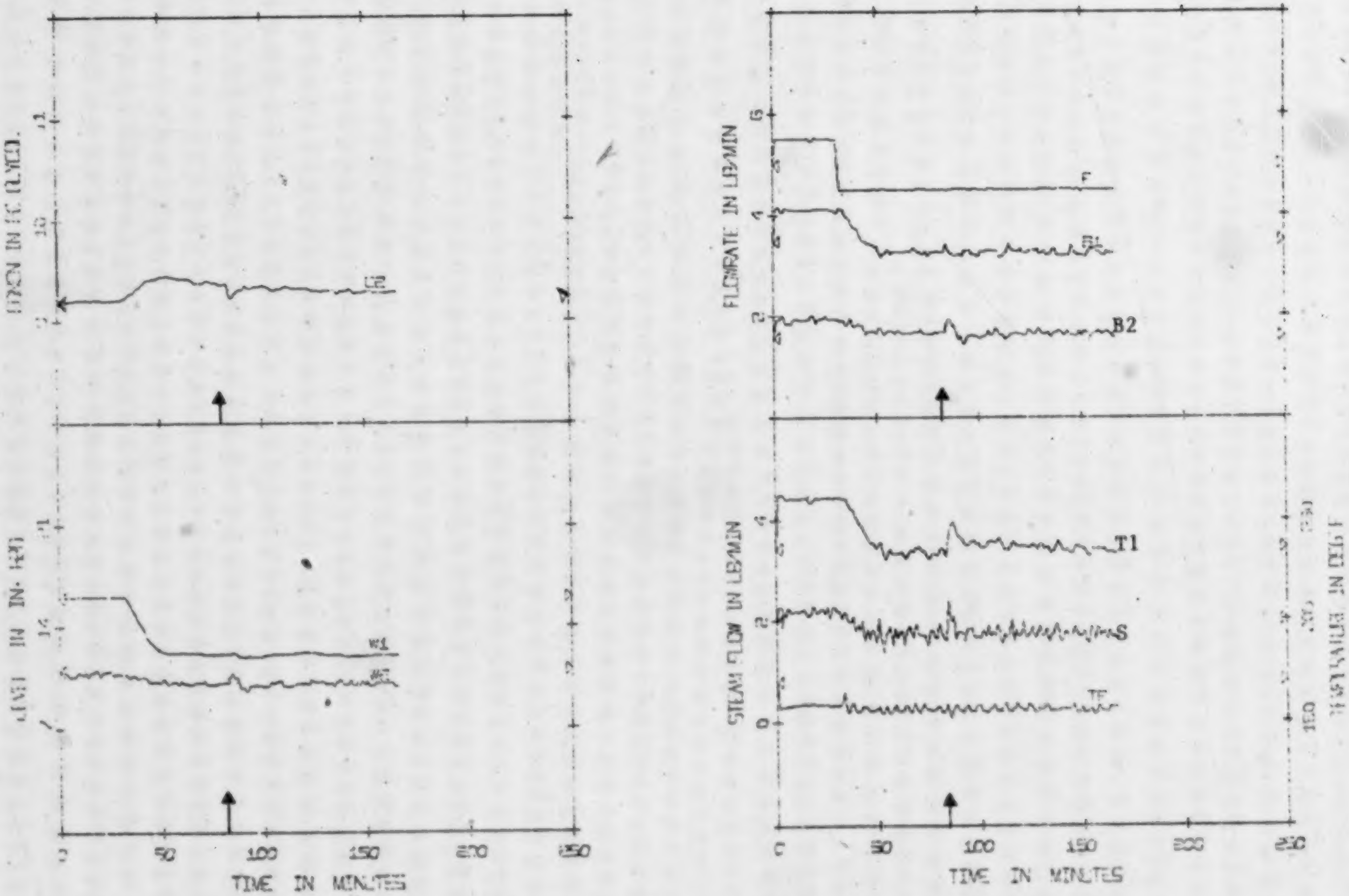

FIGURE 4.29 EXPERIMENTAL RUN FS-13 : STOCHASTIC CONTROLLER #2

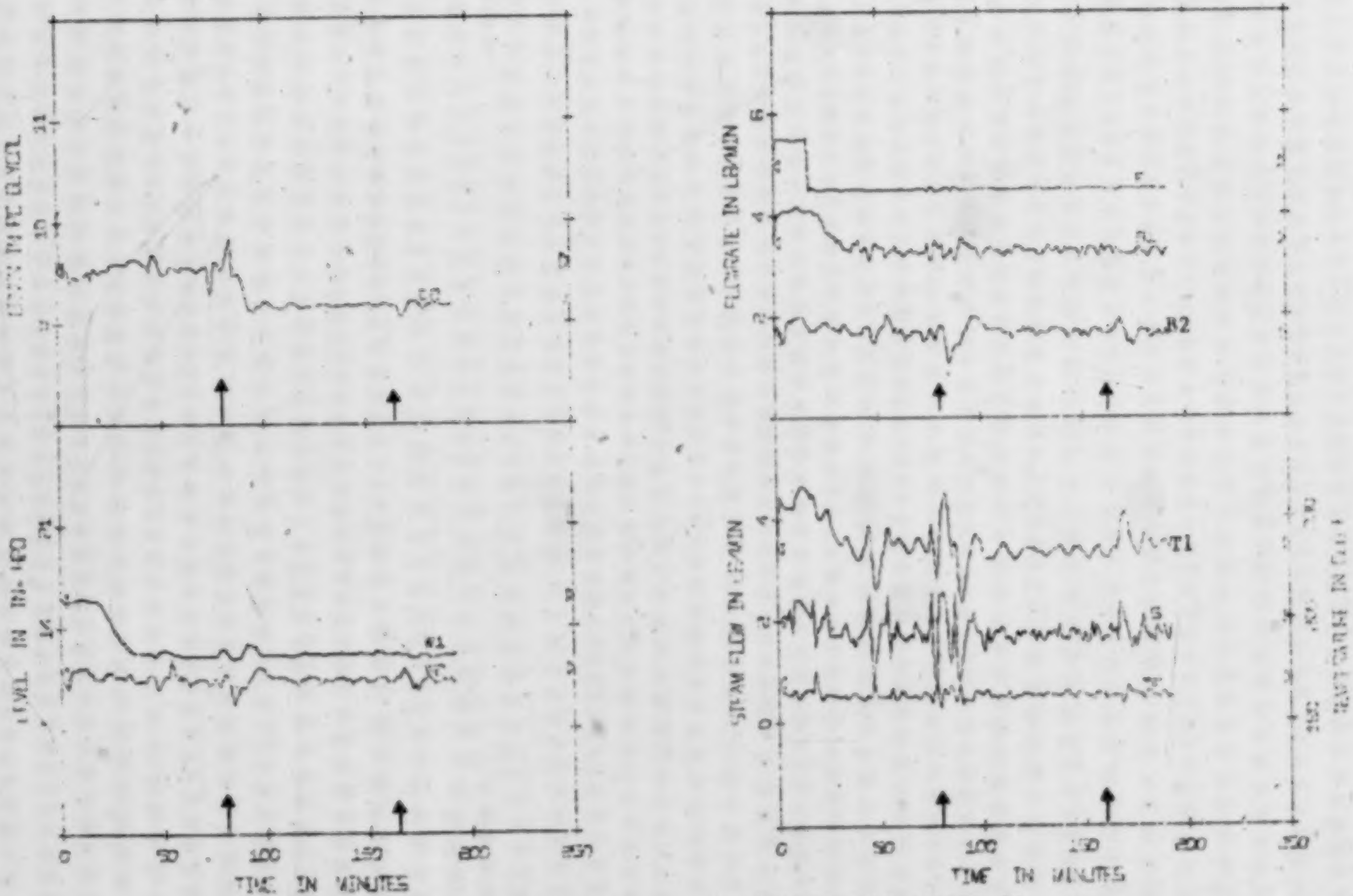

FIGURE 4.30 EXPERIMENTAL RUN FS-14 : STOCHASTIC CONTROLLER #3

5

When the three controllers were designed, noise models with one degree of differencing were used to provide integral action in the controllers and remove offsets. But since the process model has a root very near the unit circle (1.01) the effect of the (1 - B) factor providing integral action is almost nullified and the result is a controller without integral action.

4.3.4 Performance of Stochastic Controllers Based on Closed Loop Identification

The MMSE controllers designed using closed loop identification runs SF-11 to SF-14 are presented in Table 4.5. In comparison with the controllers in Table 4.3, these controllers have higher K values. Various runs were attempted using these controllers and successively decreasing the value of K to $\sim$19 but for all these runs, the stochastic controllers failed to maintain the steady state concentration even before the feed disturbances were introduced (i.e. unstable responses were obtained).

The roots of the closed loop system in Fig. 2.4 when MMSE controllers #4 - 6 were used, were studied. With the exception of MMSE #4, when each of the two other MMSE controllers was considered, the roots of the closed loop system were outside the unit circle indicating a stable closed loop system. When MMSE #4 was used, it had a root (0.7033) inside the unit circle indicating unstable behaviour.

Simulations carried out using the MMSE controllers in Table 4.5 produced oscillatory and unstable responses, both for constrained and unconstrained manipulated variables. The oscillations persisted even after reducing K by fifty percent or more.

TABLE 4.5

STOCHASTIC CONTROLLERS DESIGNED FROM EXPERIMENTAL CLOSED LOOP IDENTIFICATION RUNS

(Controller $C(B) = K\,C_o(B)$)

No.	Run No.	K	$C_o(B)$
4	SF-11	194.08	$\dfrac{1 - 1.920\,B + 1.2698\,B^2 - 0.3541\,B^3 + 0.0939\,B^4}{1 - 2.1952\,B + 1.2391\,B^2 - 0.2954\,B^3 + 0.1243\,B^4}$
5	SF-12	227.43	$\dfrac{1 - 1.658\,B + 0.878\,B^2}{1 - 1.7280\,B + 0.745\,B^2}$
6	SF-13	479.54	$\dfrac{1 - 1.176\,B + 0.2714\,B^2 - 0.295\,B^3 + 0.30748\,B^4}{1 - 0.8679\,B - 0.0902\,B^2 - 0.1156\,B^3 + 0.0837\,B^4}$
7	SF-15	205.71	$\dfrac{1 - 2.5807\,B + 1.607\,B^2 + 0.2336\,B^3 - 0.2735\,B^4}{1 + 6.0117\,B - 0.4335\,B^2 - 4.5316\,B^3 - 2.0466\,B^4}$

4.4 Conclusions

From the study of MMSE controller performance, it was concluded that in simulation study the MMSE controllers, in all but one case, handled the problem of regulatory control under stochastic and deterministic disturbances very well. Only MMSE controller #4 produced unstable responses It was also demonstrated that performance comparable to PI controllers was obtained when setpoint changes were introduced. On the other hand, the controllers based on the experimental identification runs needed some tuning before they could be successfully used. In spite of vacuum disturbances they performed, in most cases, better than PI controllers. Severe vacuum disturbances led to different final values than the setpoint value. Because of small integral action, these seem like an offset for short runs. Observation of the responses indicates that the concentrations are slowly approaching the setpoint value.

For systems with low transfer function gains and large time constants, tuning or modifying the MMSE controller may be required to provide smaller input variations.

Although the controllers based on closed loop identification performed well in the simulation study, they failed to produce stable responses in the experimental study. This indicated less reliable process model identification under closed loop conditions from the point of view of controller performance.

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

The effectiveness of the time series modelling technique proposed by Box and Jenkins [1] has been investigated using simulated and experimental data for a pilot scale evaporator. The results clearly demonstrate that this technique can be successfully employed to obtain simple, dynamic stochastic models for a high order, interacting process such as the double effect evaporator. Identification using open loop and closed loop data, produced open loop process models that are in good agreement and exhibit similar trends. Comparable sum of squares of residuals and chi square statistics indicate that both identification methods are equally efficient.

Transfer function models with model orders of (2, 1, 1) proved adequate to model the process under various types of disturbances. Autoregressive parameter estimates $\{\hat{\delta}_j\}$ were fairly insensitive to process conditions and also to the choice of noise model orders, whereas the moving average parameters, $\{\hat{\omega}_j\}$ were sensitive to changes in process conditions and to the choice of noise models. Different noise models were required to model different disturbances.

MMSE controllers designed using these models produced stable responses in the simulation study, except for one controller. However, the experimental implementation of MMSE controllers caused large adjustments in the input. Due to physical constraints on the input, tuning the controller to reduce the input variance was necessary to achieve stable responses. The controllers based on closed loop simulation data performed well in simulations, but controllers designed using models identified from closed loop experimental data were found to be unstable even after large gain reduction.

All stochastic controllers exhibiting stable responses produced smaller sum square of errors for both stochastic and deterministic disturbances than the well tuned PI controllers. However the PI controllers handled vacuum disturbances better. In the simulation study, MMSE control was successfully employed for setpoint changes. This indicates the robustness of these stochastic controllers.

It can be concluded that the time series modelling technique can be employed to obtain simple models for processes. Robust stochastic controllers can be designed from these models, but in some cases the controllers produce highly oscillatory, unstable responses.

By comparing the error standard deviations using PI control, (2 parameters) and MMSE control (∿5-7 parameters) in the experimental study, the small improvement in control does not seem to justify, from point of view of industrial applications, the use of a larger number (5 - 7) of parameters.

5.1 Recommendations for Future Work

1. For the double effect evaporator application, by treating feed flow as a measured disturbance, feedforward - feedback control can be implemented.

2. The single-input single-output analysis used in this study can be extended to multivariable systems, taking into account the process interactions.

3. As some of the MMSE controllers produced unstable or highly oscillatory response, a technique to determine the stability of the closed loop system may be developed.

4. A method of reducing the number of controller constants, without increasing the error variance significantly, needs to be developed to achieve wider applicability.

5. It was found for the application of MMSE controllers to the evaporator that the input variations required were large. In order to reduce the input adjustments a controller that minimises the quadratic cost function $E\{e_{t+k}^2 + \lambda X_t^2\}$ may be designed using the evaporator models.

NOMENCLATURE

(a) Alphabetic

a	White noise
B	Backward shift operator
b	Dead time as whole multiples of sampling interval
B1	First effect bottoms flow rate
B2	Second effect bottoms flow rate
$\underline{C}$	Output coefficient matrix
C1	First effect concentration
C2	Second effect concentration
CF	Feed concentration
D	Dither signal
d	Degree of differencing
$\underline{d}$	Disturbance vector
E	Expectation operator
e	Error
F	Feed flow rate
H1	First effect enthalpy
HF	Feed enthalpy
K	Gain
$\underline{K}$	Gain matrix
N_t	Process noise
O1	Overhead first effect
O2	Overhead second effect
p	Order of autoregressive part of noise model
P1	First effect pressure

NOMENCLATURE (continued)

P2	Second effect pressure
Q	Chi-square statistic for autocorrelation function
q	Order of moving average part of the noise model
r	Order of denominator polynomial of the transfer function model
r_{xy}	Cross correlation function between series $\{X_t\}$ and $\{Y_t\}$
s	Steam flow rate
S	Chi-square statistic for cross correlation function
T1	Temperature of first effect
T2	Temperature of second effect
TF	Feed temperature
t	Sampling instant
$\underline{u}$	Control vector
V	Impulse weight polynomial
W1	First effect holdup
W2	Second effect holdup
X	Input variable
$\underline{x}$	State vector
Y	Output variable
$\underline{y}$	Output vector

(b) Greek

α	Prewhitened input
β	Transformed output

NOMENCLATURE (continued)

χ^2	Chi-square statistic
δ	Polynomial
ϕ	Autoregressive polynomial in noise model
ϕ	Partial autocorrelation
γ	Autocorrelation function
λ	Polynomial
μ	Mean value
η	Polynomial
ρ	Correlation function
Σ	Summation operator
σ	Standard deviation
ψ	Polynomial
θ	Moving average polynomial in noise model
$\underline{\underline{\theta}}$	Disturbance coefficient matrix

(c) Subscripts

i	i^{th} element
t	t^{th} sampling instant
x	Pertaining to variable x, (i.e. σ_x - standard deviation of x)
ss	Steady state
$\underline{}$	Vector
$\underline{\underline{}}$	Matrix
αa	Between series $\{\alpha_t\}$ and $\{a_t\}$

NOMENCLATURE (continued)

(d) Superscripts

-1	Matrix inverse
^	Estimated value
'	Normalized value
T	Matrix transpose

(e) Abbreviations

a.c.f.	Auto correlation function
c.c.f.	Cross correlation function
CC	Concentration controller
CR	Concentration recorder
C.I.	Confidence interval
FC	Flow controller
FR	Flow recorder
KI	Integral constant
KP	Proportional constant
LC	Level controller
LR	Level recorder
MMSE	Minimum mean square error
PI	Proportional plus integral
p.a.c.f.	Partial auto correlation function

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APPENDIX A

THE EVAPORATOR MODEL

The fifth-order discrete state-space evaporator model calculated by Wilson [20] is represented as:

$$\underline{x}(t + 1) = \underline{\phi}\,\underline{x}(t) + \underline{\Delta}\,\underline{u}(t) + \underline{\theta}\,\underline{d}(t) \qquad (A.1)$$

$$\underline{y}(t) = \underline{C}\,\underline{x}(t) \qquad (A.2)$$

The elements of the vectors $\underline{x}$, $\underline{u}$, $\underline{d}$, $\underline{y}$ are defined as normalized perturbation variables, e.g.

$$x_1 = \frac{W1 - W1_{ss}}{W1_{ss}}$$

Where $W1_{ss}$ is the normal steady state value of W1. The vectors $\underline{x}$, $\underline{u}$, $\underline{d}$ and $\underline{y}$ are defined as follows:

State Vector, $\underline{x}$	Normal Steady State Value
$\underline{x}^T$ = [W1, C1, H1, W2, C2]	
W1 First effect holdup	45.5 lb
C1 First effect concentration	4.59% glycol
H1 First effect enthalpy	189.2 BTU/lb
W2 Second effect holdup	41.5 lb
C2 Second effect concentration	10.11% glycol

Control Vector, $\underline{u}$

$\underline{u}^T = [S, B1, B2]$

S	Steam flow	2.0 lb /min
B1	First effect bottoms flow	3.485 lb /min
B2	Second effect bottoms flow	1.581 lb /min

Disturbance Vector, $\underline{d}$

$\underline{d}^T = [F, CF, HF]$

F	Feed Flow	5.0 lb /min
CF	Feed concentration	3.2% glycol
HF	Feed enthalpy	156.9 BTU/lb

Output Vector, $\underline{y}$

$\underline{y}^T = [W1, W2, C2]$

The coefficient matrices of the discrete-time model, with a 64 second time base, are shown in Table A.1.

TABLE A.1

FIFTH ORDER DISCRETE EVAPORATOR MODEL (T = 64 sec.)

$$\underline{\Phi} = \begin{bmatrix} 1 & -0.0008 & -0.0912 & 0 & 0 \\ 0 & 0.9223 & 0.0871 & 0 & 0 \\ 0 & -0.0042 & 0.4376 & 0 & 0 \\ 0 & -0.0009 & -0.1052 & 1. & 0.0001 \\ 0 & 0.0391 & 0.1048 & 0 & 0.9603 \end{bmatrix}$$

$$\underline{\Delta} = \begin{bmatrix} -0.0119 & -0.0817 & 0 \\ 0.0116 & 0 & 0 \\ 0.0116 & 0 & 0 \\ -0.0318 & 0.0848 & -0.0406 \\ 0.0137 & -0.0432 & 0 \end{bmatrix} \qquad \underline{\Theta} = \begin{bmatrix} 0.1182 & 0 & -0.0050 \\ -0.0351 & 0.0785 & 0.0049 \\ -0.0136 & -0.0002 & 0.0662 \\ 0.0012 & 0 & -0.0058 \\ -0.0019 & 0.0016 & 0.0058 \end{bmatrix}$$

$$\underline{C} = \begin{bmatrix} 1. & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1. & 0 \\ 0 & 0 & 0 & 0 & 1. \end{bmatrix}$$

APPENDIX B

CALCULATION OF OPEN LOOP PROCESS MODEL FROM A MODEL IDENTIFIED UNDER CLOSED LOOP CONDITIONS

Figure 2.3 and eqn. (2.23) indicate that the closed loop model relating dither signal D_t and output, Y_t is the identified model:

$$Y_t = G(B)\, D_t + H(B)\, a_t \tag{B.1}$$

where

$$G(B) = \frac{V(B)}{1 - C(B)\, V(B)} \tag{B.2}$$

$$H(B) = \frac{\psi(B)}{1 - C(B)\, V(B)} \tag{B.3}$$

and

C(B) = controller transfer function.

V(B) = open loop process transfer function model.

ψ(B) = open loop noise model.

G(B) = closed loop process transfer function model.

H(B) = noise model obtained under closed loop conditions.

Equation (B.2) can be rearranged as,

$$V(B) = \frac{G(B)}{1 + C(B)\, G(B)} \tag{B.4}$$

For closed loop experiment run # SF-13 in Table 3.19

$$G(B) = \frac{(1.08 + 0.378\ B) \times 10^{-3}\ B}{1 - 1.697\ B + 0.755\ B^2} \qquad (B.5)$$

The proportional controller gain used during closed loop operation was K = -2.5. Then substituting eqns. (B.5) and (B.6) into (B.4) gives:

$$V(B) = \frac{(1.08 + 0.378\ B)\ B \times 10^{-3}}{1 - 1.70\ B + 0.754\ B^2} \qquad (B.6)$$

and

$$1 - V(B)\ C(B) =$$
$$\frac{1 - 1.700\ B + 0.754\ B^2 + 2.5\ (1.08\ B + 0.378\ B^2) \times 10^{-3}}{1 - 1.703\ B + 0.754\ B^2} \qquad (B.7)$$

Since the numerator and denominator of (1 - V(B) C(B)) are almost identical,

$$1 - V(B)\ C(B) \cong 1 \qquad (B.8)$$

hence

$$\psi(B) = H(B) = \frac{1}{(1 - 0.4821\ B - 0.2106\ B^2)\ (1 - B)} \qquad (B.9)$$

The complete open loop process model is:

$$Y_t = \frac{(1.08 + 0.378B) \times 10^{-3}}{1 - 1.799\ B + 0.754\ B^2} X_{t-1} + \frac{1}{(1 - 0.4821\ B - 0.2106\ B^2)(1-B)} a_t \tag{B.10}$$

APPENDIX C

MMSE CONTROLLER DESIGN

The process model identified for simulation run SSF-1 is presented in Table 3.4. Using the procedure outlined in §2.3 a minimum mean square error feedback controller is designed as follows.

The process model has orders (2, 1, 1) for the transfer function part and orders (1, 1, 1) for the noise model.

$$Y_{t+} = \frac{0.01363 + 0.009609\ B}{(1 - 1.51\ B + 0.5151\ B^2)}\ X_{t-1} + N_t \qquad (C.1)$$

and

$$N_t = \frac{(1 - 0.1808\ B)}{(1 - 0.8704\ B)\ (1 - B)}\ a_t \qquad (C.2)$$

Therefore

$$N_{t+1} = a_{t+1} + \frac{1.6896 - 0.8704\ B}{(1 - 1.8704\ B + 0.8704\ B^2)}\ a_t \qquad (C.3)$$

hence

$$\eta(B) = \frac{1.6896 - 0.8704\ B}{(1 - 1.8704\ B + 0.8704\ B^2)} \qquad (C.4)$$

and

$$\lambda(B) = 1 \qquad (C.5)$$

Using eqn. (2.30) the MMSE controller obtained is then,

$$C(B) = \frac{-\delta(B)\ \eta(B)}{\omega(B)\ \lambda(B)}$$

$$= \frac{-(1 - 1.51\ B + 0.5151\ B^2)\ (1.6896 - 0.8704\ B)}{(0.01363 + 0.009609\ B)\ (1 - 1.8704 + 0.8704\ B^2)}$$

$$= \frac{-123.96\ (1 - 2.025\ B + 1.2930\ B^2 - 0.2654\ B^3)}{(1 - 1.1654\ B - 0.4482\ B^2 + 0.6136\ B^3)} \qquad (C.6)$$

The control law for this controller is,

$$X_{t+} = -123.96\ (e_t - 2.025\ e_{t-1} + 1.293\ e_{t-2} - 0.2654\ e_{t-3})$$

$$+ (1.1654\ X_{t-1} + 0.4482\ X_{t-2} - 0.6136\ X_{t-3}) \qquad (C.7)$$

APPENDIX D

RESULTS FROM PARAMETER ESTIMATION

Model	$\hat{\delta}_1$	$\hat{\delta}_2$	$\hat{\omega}_0$	$\hat{\omega}_1$	$\hat{\phi}_1$	$\hat{\phi}_2$	$\hat{\theta}_1$	$S_{\alpha a}$	Q_a	Σa_t^2
RUN SS-4										
(2 1 1)[1]	1.539	-0.5787	-0.00527	-0.03619	---	---	---	15.66	---	5.80
(0 0 0)[2]	1.557	-0.5491	0.02004	-0.01032	---	---	--- **			
	1.521	-0.6083	-0.03059	-0.06206	---	---	--- **			
(2 1 1)	1.689	-0.7587	0.00960	-0.00433	0.9176	---	0.2071	8.67	47.65	3.42
(1 0 1)	1.779	-0.6777	0.03175	0.01782	1.0110	---	0.3525			
	1.598	-0.8397	-0.01248	-0.02648	0·824	---	0.0618			
(2 1 1)	1.600	-0.6097	0.01481	-0.00812	-0.7693	-0.1045	-0.5712	8.64	65.16	1.65
(2 0 1)	1.600	-0.6077	0.02694	0.00447	-0.6999	-0.0226	-0.4340			
	1.599	-0.6117	0·0029	-0.20700	-0.8390	-0.1863	-0.7083			
RUN SS-5										
(2 1 1)	1.548	-0.5589	0.01030	-0.01560	-0.0535	0.5298	-0.5352	12.99	28.66	0.61
(2 0 1)	1.548	-0.5569	0.02230	-0.00317	0.0200	0.6205	-0.4282			
	1.547	-0.5610	-0.00170	-0.02810	-0.1271	0.4390	-0.6422			
RUN SS-6										
(2 1 1)	1.628	-0.6377	0.01481	-0.00669	-0.3178	0.1748	-0.4738	11.25	34.34	1.36
(2 0 1)	1.628	-0.6362	0.02487	0.00387	-0.2748	0.2891	-0.3489			
	1.628	-0.6392	0.00476	-0.01707	-0.3607	0.0605	-0.5987			

[1] Process transfer function model orders, (r, s, b).

[2] Noise model orders, (p, d, q)

** 95 percent confidence limits for the parameter estimates.

	$\hat{\delta}_1$	$\hat{\delta}_2$	$\hat{\omega}_0$	$\hat{\omega}_1$	$\hat{\phi}_1$	$\hat{\phi}_2$	$\hat{\theta}_1$	S_{aa}	Q_a	$\Sigma a_t^2 \times 10^4$
RUN SSF-1										
(2 1 1)	1.510	-0.5140	0.01370	-0.00942	0.9048	---	---	28.99	26.41	1.75
(1 1 0)	1.500	-0.5088	0.01419	-0.00896	0.9506	---	---			
	1.510	-0.5192	-0.01322	-0.00988	0.8584	---	---			
(2 1 1)	1.510	-0.5151	0.01363	-0.00961	0.8704	---	-0.1808	28.77	23.53	1.32
(1 1 1)	1.510	-0.5100	0.01412	-0.00914	0.9299	---	-0.5912			
	1.509	-0.5202	0.01315	-0.01008	0.8109	---	-0.2025			
RUN SSF-2										
(2 1 1)	1.510	-0.5147	0.01367	-0.00940	0.9634	---	---	31.63	93.63	1.71
(1 1 0)	1.510	-0.5097	0.01429	-0.00879	0.9945	---	---			
	1.510	-0.5198	0.01306	-0.01000	0.9322	---	---			
(2 1 1)	1.509	-0.5141	0.01350	-0.00918	0.9431	---	-0.4759	28.87	30.08	1.68
(1 1 1)	1.510	-0.5085	0.01404	-0.00824	0.9837	---	-0.3742			
	1.509	-0.5198	0.01296	-0.01032	0.9025	---	-0.5778			
RUN SSF-3										
(2 1 1)	1.509	-0.5146	0.01371	-0.00980	0.9819	---	---	24.00	179.14	2.67
(1 1 0)	1.509	-0.5078	0.01423	-0.00928	1.0060	---	---			
	1.509	-0.5215	0.01390	-0.01037	0.9578	---	---			
(2 1 1)	1.444	-0.4721	0.01283	-0.00992	1.6490	-0.6859	---	22.97	25.77	1.58
(2 1 0)	1.462	-0.4480	0.01315	-0.00953	1.7300	-0.5995	---			
	1.426	-0.4962	0.01250	-0.01032	1.5630	-0.7723	---			
(2 1 1)	1.509	-0.5130	0.01361	-0.01014	0.9697	---	-0.5966	26.27	50.57	1.69
(1 1 1)	1.509	-0.5026	0.01403	-0.00971	1.0010	---	-0.5049			
	1.509	-0.5204	0.01319	-0.01057	0.9388	---	-0.6883			
(2 1 1)	1.440	-0.4649	0.01289	-0.00996	1.4960	-0.5360	-0.2681	21.79	22.85	1.55
(2 1 1)	1.456	-0.4423	0.01323	-0.00958	1.6400	-0.3932	-0.1098			
	1.424	-0.4876	0.01255	-0.10350	1.3520	-0.6788	-0.4265			
RUN SSF-4										
(2 1 1)	1.509	-0.5011	0.01449	-0.01050	0.9865	---	---	21.89	203.11	2.09
(1 1 0)	1.509	-0.4838	0.01578	-0.00978	1.0090	---	---			
	1.509	-0.5183	0.01321	-0.01140	0.9639	---	---			
(2 1 1)	1.366	-0.4649	0.01215	-0.00987	1.6570	-0.6954	---	26.78	25.27	2.99
(2 1 0)	1.435	-0.3919	0.01311	-0.00878	1.7390	-0.6135	---			
	1.296	-0.5380	0.01119	-0.01094	1.5760	-0.7772	---			
(2 1 1)	1.365	-0.4527	0.01239	-0.01000	1.5390	-0.5789	-0.2270	25.99	20.97	2.90
(2 1 1)	1.438	-0.3750	0.01337	-0.00895	1.6680	-0.4509	-0.0740			
	1.291	-0.5304	0.01142	-0.01105	1.4100	-0.7070	-0.3801			

	$\hat{\delta}_1$	$\hat{\delta}_2$	$\hat{\omega}_0$	$\hat{\omega}_1$	$\hat{\phi}_1$	$\hat{\phi}_2$	$\hat{\theta}_1$	S_{aa}	Q_a	Σa_t^2 x10^4
RUN SSF-11										
(2 1 1)	1.403	-0.4487	0.01389	-0.01126	0.8550	---	-0.5114	11.19	40.13	2.94
(1 1 1)	1.457 1.349	-0.3808 -0.5085	0.01501 0.01276	-0.00993 -0.01259	0.9174 0.0793	--- ---	-0.4093 -0.6136			
(2 1 1)	1.393	-0.4353	0.01412	-0.01148	0.9104	---	---	9.96	130.41	4.02
(1 1 0)	1.446 1.340	-0.3774 -0.4932	0.01544 0.01280	-0.00980 -0.01316	0.9575 0.8633	--- ---	--- ---			
(2 1 1)	1.375	-0.4372	0.01312	-0.01115	1.2410	-0.4014	-0.2578	16.00	21.65	2.87
(2 1 1)	1.439 1.311	-0.3654 -0.5089	0.01420 0.01205	-0.00987 -0.01242	1.4180 1.0630	-0.2314 -0.5714	-0.0735 -0.4421			
RUN SSF-12										
(2 1 1)	1.411	-0.4681	0.01340	-0.01048	1.8390	-0.8550	---	36.87	40.47	1.44
(2 0 0)	1.443 1.378	-0.4308 -0.5053	0.01394 0.01235	-0.00945 -0.01151	1.9000 1.7780	-0.7947 -0.9154	--- ---			
(2 1 1)	1.442	-0.4964	0.01356	-0.00969	0.7755	---	-0.2937	24.96	23.94	1.38
(1 1 1)	1.475 1.409	-0.4600 -0.5529	0.01434 0.01278	-0.00874 -0.01064	0.8610 0.6901	--- ---	-0.1693 -0.4182			
(2 1 1)	1.446	-0.5006	0.01368	-0.00954	1.0470	-0.2232	---	24.82	23.56	1.33
(2 1 0)	1.481 1.411	-0.4628 -0.5384	0.01439 0.01292	-0.008577 -0.01050	1.1570 0.9363	-0.1123 0.3342	--- ---			
RUN SSF-13										
(2 1 1)	1.423	-0.4735	0.01385	-0.01084	0.9268	---	---	9.92	123.60	1.08
(1 1 0)	1.443 1.404	-0.4523 -0.4946	0.01430 0.01339	-0.01024 -0.01144	0.9702 0.8829	--- ---	--- ---			
(2 1 1)	1.427	-0.4790	0.01376	-0.10710	0.8756	---	-0.4973	10.96	39.03	0.80
(1 1 1)	1.447 1.407	-0.4572 -0.5009	0.01415 0.01337	-0.01024 -0.01118	0.9339 0.8172	--- ---	-0.3949 -0.5997			
(2 1 1)	1.444	-0.4954	0.01351	-0.01040	1.4140	-0.5492	---	14.45	27.53	0.76
(2 1 0)	1.459 1.416	-0.4723 -0.5165	0.01386 0.01315	-0.00995 -0.[illegible]0850	1.5080 1.3190	-0.4548 -0.6435	--- ---			
(2 1 1)	1.415	-0.4717	0.01352	-0.01067	1.3110	-0.4475	-0.1911	16.16	22.63	0.78
(2 1 1)	1.437 1.393	-0.4467 -0.4966	0.01388 0.01315	-0.01023 -0.01112	1.4870 1.1360	-0.2789 -0.6162	0.0005 -0.3828			

	$\hat{\delta}_1$	$\hat{\delta}_2$	$\hat{\omega}_0$	$\hat{\omega}_1$	$\hat{\phi}_1$	$\hat{\phi}_2$	$\hat{\theta}_1$	$S_{\alpha a}$	Q_a	Σa_t^2
RUN SSF-14										$\times 10^4$
(2 1 1 1)	1.432	-0.4870	0.01356	-0.01074	0.7965	---	-0.2668	24.60	19.78	1.35
(1 1 1 1)	1.456	-0.4608	0.01407	-0.01007	0.8830	---	-0.1345			
	1.408	-0.5134	0.01304	-0.01140	0.7100	---	-0.3865			
(2 1 1 1)	1.447	-0.5004	0.01357	-0.01034	0.8868	---	---	22.87	31.91	1.40
(1 1 0)	1.469	-0.4764	0.01409	-0.00964	0.9319	---	---			
	1.425	-0.5243	0.01305	-0.01103	0.8051	---	---			
RUN SSF-15										
(2 1 1 1)	1.412	-0.4624	0.01375	-0.01097	0.8715	-0.0	-0.5025	11.89	41.44	1.40
(1 1 1 1)	1.439	-0.4332	0.01427	-0.01034	0.9317	---	-0.4002			
	1.385	-0.4916	0.01323	-0.01199	0.8116	---	-0.6048			
(2 1 1 1)	1.402	-0.4602	0.01329	-0.01082	1.2190	-0.3716	-0.2871	17.36	28.76	1.42
(2 1 1 1)	1.432	-0.4260	0.01380	-0.01022	1.3970	-0.1997	-0.1092			
	1.372	-0.4940	0.01280	-0.01143	1.0420	-0.5435	-0.4649			
RUN SSF-16										
(2 1 1 1)	1.423	-0.4758	0.01378	-0.01065	0.7659	---	-0.2322	14.94	19.69	0.74
(1 1 1 1)	1.442	-0.4550	0.01416	-0.01018	0.8553	---	-0.1018			
	1.404	-0.4966	0.01340	-0.01112	0.6765	---	-0.3626			
(2 1 1 1)	1.424	-0.4811	0.01337	-0.01066	0.9767	-0.1960	---	18.82	27.53	0.81
(2 1 0)	1.444	-0.4592	0.01374	-0.01017	1.0930	-0.0795	---			
	1.404	-0.5030	0.01301	-0.01116	0.8600	-0.0312	---			
RUN SSF-17										
(2 1 1 1)	1.425	-0.4751	0.01382	-0.01071	0.8552	---	-0.4908	10.37	30.62	0.77
(1 1 1 1)	1.447	-0.4522	0.01420	-0.01027	0.9174		-0.3873			
	1.404	-0.4980	0.01343	-0.01114	0.7929	---	-0.5948			
(2 1 1 1)	1.423	-0.4830	0.01340	-0.01047	1.4080	-0.5570	---	15.25	25.01	0.76
(2 1 0)	1.447	-0.4571	0.01375	-0.01005	1.5050	-0.4600	---			
	1.404	-0.5088	0.01308	-0.01088	1.3110	-0.6540	---			
(2 1 1 1)	1.423	-0.4782	0.01350	-0.01045	1.2646	-0.4074	-0.2125	14.03	20.94	0.75
(2 1 1 1)	1.444	-0.4526	0.01386	-0.01013	1.4310	-0.2316	-0.0190			
	1.397	-0.5039	0.01313	-0.01095	1.0620	-0.5832	-0.4060			

Model	δ_1	δ_2	ω_0	ω_1	ϕ_1	ϕ_2	θ_1	S_{aa}	Q_a	Σa_t^2
RUN S-1			$\times 10^2$	$\times 10^3$						$\times 10^2$
(2 1 1)	1.700	-0.7030	0.5701	1.6126	---	---	---	17.65	---	17.28
(0 0 0)	1.700 1.700	-0.7000 -0.7060	1.8036 -0.6646	1.3563 -1.0327	--- ---	--- ---	--- ---			
(2 1 1)	1.700	-0.7027	0.9396	-0.4860	0.8840	0.1010	---	17.22	38.19	0.43
(2 0 0)	1.700 1.700	-0.6970 -0.7088	1.1515 0.7281	0.9489 -1.924	0.9041 0.7738	0.2119 -0.0082	--- ---			
(2 1 1)	1.700	-0.7043	0.8264	-1.2600	-0.1172	-0.1330	---	18.84	32.41	0.44
(2 1 0)	1.700 1.700	-0.6985 -0.7102	1.0818 0.5544	1.7472 -4.0720	-0.0031 -0.2310	-0.0287 -0.2374	--- ---			
(2 1 1)	1.700	-0.7030	0.9990	0.2484	1.0130	-0.2460	0.1340	16.88	37.61	0.43
(2 0 1)	1.700 1.700	-0.6970 -0.7085	1.2672 0.7306	2.8808 -2.5380	1.4880 0.5457	0.4317 -0.4808	0.6054 -0.3380			
(2 1 1)	1.700	-0.7028	0.9392	-0.5499	-0.1072	---	---	17.62	39.60	0.43
(1 1 0)	1.700 1.700	-0.6998 -0.7083	1.1488 0.7277	0.8624 -1.9620	0.0023 -0.2168	--- ---	--- ---			
RUN S-2										
(2 1 1)	1.700	-0.7041	0.7495	-1.2386	0.8496	0.0970	---	25.99	11.89	0.73
(2 0 0)	1.700 1.700	-0.7013 -0.7010	0.9572 0.6416	0.6300 -3.3192	0.9824 0.7768	-0.2005 -0.0059	--- ---			
(2 1 1)	1.700	-0.7038	0.7740	-1.1340	-0.0968	---	---	24.09	11.76	0.73
(1 1 0)	1.700 1.700	-0.7011 -0.7064	0.9773 0.5706	0.7866 -3.0546	0.0058 0.1997	--- ---	--- ---			
RUN S-3										
(2 1 1)	1.692	-0.7180	0.6642	0.8946	1.3310	-0.3950	---	20.69	66.84	0.19
(2 0 0)	1.703 1.682	-0.7000 -0.7350	0.8175 0.2510	2.4408 -0.8023	1.4860 1.6630	-0.2032 -0.4508	--- ---			
(2 1 1)	1.699	-0.7100	0.6925	0.5838	1.9180	-0.9217	0.7350	19.89	19.85	0.18
(2 0 1)	1.699 1.699	-0.6990 -0.7212	0.3305 0.5524	1.9692 -0.8023	1.9740 1.8530	-0.8670 -0.9756	0.8416 0.6285			
(2 1 1)	1.683	-0.7135	0.6683	0.9515	0.4267	---	---	19.50	77.02	0.19
(1 1 0)	1.703 1.664	-0.6832 -0.7438	0.8197 0.5109	2.4930 -0.6922	0.5279 0.1991	--- ---	--- ---			

	$\hat{\delta}_1$	$\hat{\delta}_2$	$\hat{\omega}_0$	$\hat{\omega}_1$	$\hat{\phi}_1$	$\hat{\phi}_2$	$\hat{\theta}_1$	$S_{\alpha a}$		Σa_t^2
RUN S-4			x10^2	x10^3						x10^2
(2 1 1 1)	1.700	-0.7661	0.8320	-2.9394	0.7951	0.1974	---	20.69	21.34	1.03
(2 0 0 1)	1.700	-0.7082	0.9196	-0.1139	0.9010	0.2031	---			
	1.700	-0.7098	0.3276	-5.8662	0.6056	0.5968	---			
(2 1 1 1)	1.700	-0.7064	0.8113	-3.2490	-0.1924	---	---	20.55	20.33	1.04
(1 1 0 1)	1.700	-0.7028	0.9090	-0.3416	-0.0859	---	---			
	1.700	0.7101	0.3132	-6.1578	-0.2989	---	---			
RUN SF-1										
(2 1 1 1)	1.700	-0.7080	0.0346	9.8802	0.8738	---	---	21.48	25.21	0.81
(1 0 0)	1.700	-0.7033	0.7659	-2.0898	0.9361	---	---			
	1.700	-0.7087	-0.6988	-17.6724	0.8115	---	---			
(2 1 1 1)	1.700	-0.7041	1.1848	2.2150	-0.2210	---	---	14.80	23.90	0.79
(1 1 0)	1.700	-0.6966	1.2488	8.2278	-0.1121	---	---			
	1.700	-0.7097	0.8227	-3.7944	-0.3298	---	---			
RUN SF-2										
(2 1 1 1)	1.700	-0.7094	-0.7489	-23.5980	0.7282	---	---	40.69	31.81	2.12
(1 0 0)	1.700	-0.7068	3.1885	-1.5118	0.8115	---	---			
	1.700	-0.7120	1.6748	-32.0760	0.6449	---	---			
(2 1 1 1)	1.807	-0.9116	-0.1693	-4.6890	0.8060	0.1577	---	36.93	23.68	2.29
(2 0 0)	1.837	-0.8856	0.4525	1.5102	0.9180	0.2688	---			
	1.701	-0.9378	-0.7911	-10.6720	0.6941	0.0467	---			
(2 1 1)	1.699	-0.7084	-0.9176	-25.3800	0.7575	---	0.0573	43.43	28.11	2.18
(1 0 1)	1.699	0.7085	-0.0071	-17.1324	0.8640	---	0.2136			
	1.699	-0.7112	-1.8288	-33.6600	0.6510	---	-0.0989			
(2 1 1 1)	1.804	-0.9151	0.1624	-4.0626	0.1582	---	0.3384	41.15	23.23	2.23
(1 1 1 1)	1.837	-0.8844	0.4262	1.8108	0.7473	---	0.9021			
	1.771	-0.9458	-0.7510	-9.9360	-0.4309	---	-0.2252			
RUN SF-3										
(2 1 1)	1.700	-0.7050	0.9322	-2.0880	-0.2263	---	---	15.95	73.75	0.11
(1 1 0)	1.700	-0.7038	1.1311	0.0137	-0.1426	---	---			
	1.700	-0.7084	0.7325	-4.1904	-0.3100	---	---			
(2 1 1)	1.700	-0.7085	0.5985	-2.9232	0.9945	---	-0.0696	12.28	316.80	0.18
(1 0 1)	1.700	-0.7055	0.9182	0.3627	1.0120	---	0.0440			
	1.700	-0.7110	0.2788	-6.2082	0.9770	---	-0.1840			
(2 1 1 1)	1.700	-0.7045	0.9579	-1.599	-0.2384	---	-0.0142	14.10	85.17	0.11
(1 1 1 1)	1.700	-0.7030	1.1761	0.5058	-0.0940	---	0.1777			
	1.700	-0.7060	0.7393	-3.9060	-0.3757	---	-0.2069			

	$\hat{\delta}_1$	$\hat{\delta}_2$	$\hat{\omega}_0$ $x10^2$	$\hat{\omega}_1$ $x10^3$	$\hat{\phi}_1$	$\hat{\phi}_2$	$\hat{\theta}_1$	$S_{\alpha a}$		Σa_t^2 $x10^2$
RUN SF-4										
(2 1 1)	1.700	-0.7063	0.6556	-6.8320	0.9058	-0.0110	---	39.28	68.15	0.27
(2 0 0)	1.700 1.700	-0.7049 -0.7077	1.0395 0.2714	-2.0106 -9.6534	1.0140 0.7976	0.0815 -0.1036	--- ---			
(2 1 1)	1.700	-0.7650	0.9872	-1.6196	0.5566	---	0.6487	25.44	37.77	0.23
(1 1 1)	1.700 1.700	-0.7028 -0.7071	1.3156 0.5999	1.9270 -5.166	0.6237 0.4895	--- ---	0.7747 0.5271			
(2 1 1)	1.700	-0.7065	1.0525	-2.6550	0.8267	---	-0.0867	35.66	116.11	0.29
(1 0 1)	1.700 1.700	-0.7055 -0.7072	1.4618 0.6233	1.7604 -7.0704	0.8549 0.7984	--- ---	0.0313 -0.2048			
RUN SF-4(1)										
(2 1 1)	1.732	-0.7373	0.5056	-3.0132	---	---	---	22.68	---	4.01
(0 0 0)	1.733 1.732	-0.7351 -0.7395	2.2140 -1.2031	14.0508 -20.0700	--- ---	--- ---	--- ---			
SF-4(2)										
(2 1 1)	1.902	-0.9077	-2.1150	-25.7220	---	---	---	85.77	---	2.91
(0 0 0)	1.902 1.902	-0.9066 -0.9088	-..4344 -2.7936	-18.7020 -32.7420	--- ---	--- ---	--- ---			
SF-4(3)										
(2 1 1)	1.731	-0.7379	0.5195	-5.7294	---	---	---	17.31	---	1.27
(0 0 0)	1.732 1.731	-0.7366 -0.7391	1.1106 -0.0718	0.6428 -12.1032	--- ---	--- ---	--- ---			
SF-4(4)										
(2 1 1)	1.726	-0.7334	0.9122	-4.6494	---	---	---	64.33	---	0.41
(0 0 0)	1.726 1.726	-0.7324 -0.7343	1.3484 0.4750	-0.8445 -8.7552	--- ---	--- ---	--- ---			
SF-4(5)										
(2 1 1)	1.733	-0.7408	0.4525	-4.3182	---	---	---	46.39	---	12.59
(0 0 0)	1.733 1.733	-0.7284 -0.7431	1.8990 -0.9940	10.5210 -19.1520	--- ---	--- ---	--- ---			
SF-4(6)										
(2 1 1)	1.724	-0.7317	0.5231	-7.2846	---	---	---	58.44	---	0.96
(0 0 0)	1.724 1.724	-0.7301 -0.7333	1.7320 -0.6858	5.2704 -19.8360	--- ---	--- ---	--- ---			

	$\hat{\delta}_1$	$\hat{\delta}_2$	$\hat{\omega}_0$ $\times 10^2$	$\hat{\omega}_1$ $\times 10^3$	$\hat{\phi}_1$	$\hat{\phi}_2$	$\hat{\theta}_1$	$S_{\alpha a}$		Σa_t^2 $\times 10^2$
SF-4(7)										
(2 1 1 1)	1.734	-0.7408	0.5863	-5.4342	---	---	---	13.20	---	1.61
(0 0 0 0)	1.734	-0.7400	0.9886	-0.9336	---	---	---			
	1.734	-0.7415	0.1478	-9.9288	---	---	---			
SF-4(8)										
(2 1 1 1)	1.727	-0.7336	0.6838	-6.3396	---	---	---	12.12	---	1.03
(0 0 0 0)	1.727	-0.7331	1.1370	-1.7494	---	---	---			
	1.727	-0.7342	0.2356	-10.9308	---	---	---			
SF-4(9)										
(2 1 1 1)	1.700	-0.7058	1.4965	3.9762	---	---	---	27.61	---	0.72
(0 0 0 0)	1.700	-0.7048	2.3004	12.2094	---	---	---			
	1.700	-0.7078	0.6881	-4.2570	---	---	---			
RUN SF-5										
(2 1 1 1)	1.863	-0.8673	1.2245	0.5742	-0.8316	---	-0.8159	20.24	96.56	2.26
(1 1 1 1)	1.863	-0.8631	2.1942	1.5714	-0.7711	---	-0.7287			
	1.863	-0.8714	0.2548	-0.4248	-0.8921	---	-0.9031			
(2 1 1 1)	1.510	0.5183	0.3248	-1.5048	-0.2399	-0.2010	---	16.31	33.78	2.08
(2 1 0 0)	1.511	-0.5114	1.3214	-0.5400	-0.1415	-0.1079	---			
	1.509	-0.5252	-0.6527	-2.4666	-0.3382	-0.2941	---			
(2 1 1 1)	1.510	-0.5180	1.1835	-1.8216	-0.0945	-0.1117	0.2015	17.24	28.15	2.05
(2 1 1 1)	1.510	-0.5117	1.0845	-0.8862	0.1032	0.0439	0.4428			
	1.509	-0.5242	-0.8478	-2.7776	-0.2922	-0.2673	-0.0797			
RUN SF-11										
(2 1 1 1)	1.708	-0.7484	0.0460	7.3778	-0.4783	---	-0.2339	24.17	41.18	1.39
(1 1 1 1)	1.780	-0.6880	0.8734	10.8234	-0.1293	---	0.1537			
	1.662	-0.8120	-0.7814	-6.0696	-0.8274	---	-0.6202			
(2 1 1 1)	1.702	-0.7503	-0.8074	30.1420	-0.2818	---	---	34.06	48.12	1.39
(1 1 0 0)	1.759	-0.6441	0.7434	9.6480	-0.1531	---	---			
	1.645	-0.9265	-2.7346	-2.6160	-0.3705	---	---			
(2 1 1 1)	1.719	-0.8115	0.3937	5.6740	-0.2326	0.0868	---	30.49	37.71	1.39
(2 1 0 0)	1.862	-0.6592	1.1530	13.1480	-0.0021	0.1998	---			
	1.575	-0.9630	-0.3672	-1.8540	-0.0003	-0.0253	---			

	$\hat{\delta}_1$	$\hat{\delta}_2$	$\hat{\omega}_0$	$\hat{\omega}_1$	$\hat{\phi}_1$	$\hat{\phi}_2$	$\hat{\theta}_1$	S_{aa}		Σa_t^2
RUN SF-12			$x10^2$	$x10^3$						$x10^2$
(2 1 1 1)	1.648	-0.8694	0.3632	3.2742	0.8261	---	---	23.45	48.49	1.75
(1 0 0 1)	2.031	-0.5042	1.0670	9.6840	0.8891	---	---			
	1.266	-1.2350	0.3406	-0.3132	0.7632	---	---			
RUN SF-13										
(2 1 1 1)	1.611	-0.6661	0.4482	4.2300	-0.2981	---	---	16.32	24.81	1.75
(1 1 1 0)	1.758	-0.4483	1.4082	14.3946	-0.2981	---	---			
	1.468	-0.8637	-0.5913	-5.9310	-0.8046	---	---			
(2 1 1 1)	1.697	-0.7550	0.1084	-0.3834	-0.4821	-0.2106	---	16.26	13.48	1.50
(2 1 0 1)	1.786	-0.6411	0.9463	8.8950	-0.2708	-0.0994	---			
	1.608	-0.8629	-3.7295	-7.8300	-0.5936	-0.3218	---			
RUN SF-14										
(2 1 1 1)	1.090	-0.1000	-1.1844	-35.5860	-0.4696	-0.1864	---	20.03	28.82	2.54
(2 1 0 1)	1.348	0.0915	-0.1255	-21.3300	-0.3576	-0.0432	---			
	0.833	-0.4515	-2.4894	-49.8600	-0.5817	-0.0270	---			
(2 1 1 1)	1.501	-0.5641	-0.3127	-16.72	-1.0450	-0.3430	-0.6004	19.82	34.18	2.40
(2 1 1 1)	1.668	-0.3834	0.6903	-7.8334	-0.7811	-0.2229	-0.3151			
	1.337	-0.7448	-1.3160	-25.5280	-1.2690	-0.4630	-0.8856			
RUN SF-15										
(2 1 1 1)	1.808	-0.9428	-2.3112	-0.9942	0.4897	---	---	23.41	73.11	0.44
(1 1 1 0)	1.833	-0.9196	-0.0250	1.7206	0.5879	---	---			
	1.783	-0.9661	-4.6764	-4.7016	0.3918	---	---			
(2 1 1 1)	1.819	-0.9233	-0.3590	-3.2608	1.4490	-0.5520	---	29.31	58.81	0.40
(2 0 0 1)	1.879	-0.4784	-0.0666	-0.1927	1.5440	-0.4368	---			
	1.759	-0.9688	-0.6834	-6.3090	1.3550	-0.6471	---			
(2 1 1 1)	1.687	-0.8491	-0.0860	1.2427	1.7380	-0.6201	0.4526	22.16	44.97	0.37
(2 0 1 1)	1.935	-0.6209	0.2174	4.4658	1.8370	-0.7287	0.6106			
	1.440	-1.0770	-0.3895	-1.9805	1.6400	-0.9114	0.2947			

	$\hat{\delta}_1$	$\hat{\delta}_2$	$\hat{\delta}_3$	$\hat{\omega}_0$	$\hat{\omega}_1$	$\hat{\omega}_2$	$\hat{\phi}_1$	$\hat{\phi}_2$	$\hat{\theta}_1$	$S_{\alpha a}$	Q_a
RUN SS-1											
(3 2 1)	2.319	-1.7090	0.3880	0.0134	0.0015	0.0078	---	---	---	44.55	---
(0 0 0)	2.319 2.319	-1.7080 -1.7100	0.3860 0.3880	0.0148 0.0135	0.0040 -0.0011	0.0092 0.0065	--- ---	--- ---	--- ---		
(0 0 0)	---	---	---	---	---	---	0.563	0.256	---	---	32.29
(2 1 0)	--- ---	--- ---	--- ---	--- ---	--- ---	--- ---	0.674 0.455	0.365 0.147	--- ---		
RUN SS-2											
(3 2 1)	2.319	-1.7090	0.3880	0.0134	0.0015	0.0079	---	---	---	90.62	---
(0 0 0)	2.319 2.319	-1.7090 -1.7100	0.3880 0.3860	0.0150 0.0118	0.0042 -0.0011	0.0093 0.0065	--- ---	--- ---	--- ---		
(0 0 0)	---	---	---	---	---	---	0.797	-0.053	---	---	26.75
(2 1 0)	--- ---	--- ---	--- ---	--- ---	--- ---	--- ---	0.909 0.665	0.060 -0.165	--- ---		
RUN SS-3											
(3 2 1)	2.319	-1.7090	0.3880	0.0139	0.0018	0.0084	0.490	0.440	---	130.06	50.54
(2 1 0)	2.319 2.319	-1.7090 -1.7090	0.3880 0.3880	0.0140 0.1333	0.0019 0.0018	0.0085 0.0084	0.598 0.392	0.549 0.345	--- ---		
RUN SSP-1											
(3 1 1)	1.514	-0.5558	0.0308	0.0037	-0.0179	---	---	---	---	14.37	---
(0 0 0)	1.514 1.513	-0.5482 -0.5634	0.0366 0.0249	0.0155 0.0010	-0.0087 -0.0272	--- ---	--- ---	--- ---	--- ---		
(3 1 1)	1.470	-0.4778	-0.0051	0.0127	-0.0101	---	0.879	---	-0.262	---	37.70
(1 1 1)	1.473 1.468	-0.4564 -0.4993	0.0120 -0.2808	0.0132 0.0122	-0.0096 -0.0107	--- ---	0.944 0.813	--- ---	-0.141 -0.383		
RUN SSP-2											
(3 1 1)	1.506	-0.5331	0.0156	0.0120	-0.0155	---	---	---	---	19.62	---
(0 0 0)	1.506 1.506	-0.5245 -0.5417	0.0223 0.0090	0.0246 -0.0039	-0.0018 -0.0291	--- ---	--- ---	--- ---	--- ---		
SSP-3(P)											
(2 2 1)	1.509	-0.5165	---	-0.0034	-0.0545	0.0221	---	---	---	5.75	---
(0 0 0)	1.509 1.509	-0.5139 -0.5190	--- ---	0.0246 -0.0414	0.0063 -0.1152	0.0541 -0.0100	--- ---	--- ---	--- ---		

	δ_1	δ_2	δ_3	ω_0	ω_1	ω_2	ϕ_1	ϕ_2	θ_1	S	θ
S-1											
(3 2 1)	1.700	-0.7000	-0.0024	0.6090	-1.7430	0.5180	---	---	---	9.36	---
(0 0 0)	1.700 1.700	-0.6960 -0.7040	0.0039 -0.0087	0.7130 0.4980	-0.9420 -2.6430	0.8470 0.1880	--- ---	--- ---	--- ---		
(3 1 1)	1.700	-0.6970	-0.0050	0.4710	-3.2310	---	---	---	5.720	---	15.30
(0 0 0)	1.700 1.700	-0.6940 -0.7000	-0.0035 -0.0069	0.8720 0.0700	-2.4437 -4.0200	--- ---	--- ---	--- ---	--- ---		
(2 2 1)	1.700	-0.7020	---	2.7230	16.3930	0.3410	---	---	---	21.74	---
(0 0 0)	1.700 1.700	-0.7002 -0.7040	--- ---	3.5130 2.0010	24.2900 8.4800	0.8900 -0.4090	--- ---	--- ---	--- ---		
FOR SSP-13											
(3 1 1)	1.598	-0.6417	0.0033	0.0155	-0.0034	---	---	---	---	9.27	---
(0 0 0)	1.595 1.574	-0.6250 -0.6583	0.0270 -0.0204	0.0181 0.0129	0.0003 -0.0071	--- ---	--- ---	--- ---	--- ---		
(3 1 1)	1.297	-0.2465	-0.1154	0.0134	-0.0127	---	0.825	---	---	20.25	29.31
(1 1 0)	1.323 1.270	-0.2057 -0.2874	-0.0983 -0.1324	0.0139 0.0130	-0.0121 -0.0133	--- ---	0.893 0.757	--- ---	--- ---		
(3 2 1)	1.593	-0.6383	-0.0009	0.0118	-0.0116	0.0056	---	---	---	6.66	---
(0 0 0)	1.604 1.582	-0.6141 -0.6624	0.0239 -0.0360	0.0150 0.0076	-0.0025 -0.0207	0.0123 -0.0010	--- ---	--- ---	--- ---		
(3 2 1)	1.364	-0.3712	-0.0525	0.0134	-0.0116	-0.0005	0.853	---	---	14.27	31.99
(1 1 0)	1.398 1.329	-0.3287 -0.4137	-0.0368 -0.0652	0.0138 0.0130	-0.0110 -0.0122	0.0003 -0.0012	0.923 0.783	--- ---	--- ---		
RUN S-1				$\times 10^2$	$\times 10^2$	$\times 10^2$					
(3 1 1)	1.666	-0.9464	0.2710	0.9420	0.1339	---	0.978	---	---	36.14	42.43
(1 0 0)	1.666 1.664	-0.9062 -0.9867	0.2933 0.2486	1.2610 0.6630	0.1787 -0.4480	--- ---	1.013 0.943	--- ---	--- ---		
(3 1 1)	1.698	-0.8248	0.1137	1.2720	0.1647	---	0.947	---	0.002	24.09	75.92
(1 1 1)	1.699 1.698	-0.7932 -0.8564	0.1400 0.0873	1.6070 0.9360	0.5040 -0.1750	--- ---	0.995 0.899	--- ---	0.123 -0.119		
RUN SF-2											
(3 1 1)	1.700	-0.7070	-0.0004	1.2840	-0.2055	---	---	---	---	---	---
(0 0 0)	1.700 1.700	-0.7032 -0.7107	0.0024 -0.3280	2.2570 0.3110	0.7554 -1.1660	--- ---	--- ---	--- ---	--- ---		
(3 1 1)	1.591	-0.7719	0.1616	1.0269	-0.4361	---	-0.291	---	---	20.85	32.71
(1 1 0)	1.599 1.582	-0.7045 -0.8393	0.2246 0.0986	2.1550 -0.1013	0.7144 -1.5865	--- ---	-0.182 -0.400	--- ---	--- ---		
(3 2 1)	1.700	-0.6[illegible]31	-0.3393	0.6491	0.3344	-0.3978	---	---	---	11.46	---
(0 0 0)	1.700 1.700	-0.6688 -0.5774	-0.0710 -0.0369	2.1312 -0.8329	2.3958 -3.0654	1.1304 1.9260	--- ---	--- ---	--- ---		
(3 2 1)	1.572	-0.9424	0.3508	1.9152	1.6731	-1.9674	-0.265	---	---	14.33	31.11
(1 1 0)	1.586 1.557	-0.8577 -1.0270	0.4317 0.2698	3.2220 0.6071	3.5352 -0.1885	-0.6182 -3.3210	-0.156 -0.374	--- ---	--- ---		